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The challenge of measuring labor market discrimination against women

Ronald L. Oaxaca*

Summary

■ This paper is an essay on the challenges that arise when attempting to quantify the extent of labor market discrimination against women. Three major economic theories of labor market discrimination are discussed: tastes and preferences, market power, and statistical discrimination. Decomposition methodology is presented and critiqued. Issues associated with attempts to use decomposition methodology to correct gender salary inequities in the work place are carefully examined. ■

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Equitable treatment of women has attained the status of a global social issue. For example the United Nations (UN) has established commissions and committees to address the status of women, e.g. Commission on the Status of Women (CSW); the Inter-Agency Network on Women and Gender Equality (IANWGE); Division for the Advancement of Women (DAW); Committee to Eliminate Discrimination Against Women (CEDAW). The UN proclaimed International Women's Day as a "United Nations Day for Women's Rights and International Peace" (March 8, 2006). There have been UN resolutions regarding women's rights, e.g. General Assembly Resolution 34/180 of 18 December 1979, General Assembly Resolution A/54/4 on 6 October 1999.[1] Many nations have enacted laws that attempt to address gender equity issues.

While the degree of the commitment of a society to gender equality is a major determinant of how successful anti-discrimination laws are in bringing about gender equity, another factor is the availability of appropriate methods for measuring discrimination. This of course depends on some consensus of what discrimination actually means. Such a consensus, or lack thereof, can vary across nations and over time. Technical aspects of measurement techniques are largely moot if common agreement is lacking on what constitutes gender discrimination. Labor market discrimination is arguably the single most important gender equity issue for industrialized nations. In this paper I explore the challenges faced by economists in attempting to apply economic analysis to the measurement of labor market discrimination against women.

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[1] Further information regarding the UN's involvement in women's rights can be found at the website www.un.org/issues/m-women.html.

I begin by attempting to formulate some conception of what is meant by discrimination. The New Oxford American Dictionary defines 'discrimination' as "The unjust or prejudicial treatment of different categories of people or things especially on grounds of age, race, or sex." Even if there exists a consensus as to what is meant by discrimination, "the devil is in the details" as they say. One can imagine instances in which men and women are treated unequally in some domain, but the disparate treatment is socially acceptable (and legal). Examples may be found under the heading of statistical discrimination which is discussed later in the paper.

In the labor market context, one might argue at some level that discrimination is manifested by a gender wage gap that remains after accounting for all known systematic determinants of productivity. In other words we might expect that, at least on average, a male and a female who have the same relevant qualifications should receive the same compensation. Immediately, two problems arise. First, can we agree on what the relevant qualifications are? Perhaps the only unambiguous circumstance is one in which workers are paid on a piece-rate basis. As long as the piece-rates in a given place of employment are the same for everyone, gender differences in compensation would have to arise exclusively from gender differences in productivity. Second, can we assume that on average the work and career preferences of men and women are identical? Even if it appears that men and women have different work and career preferences, how can we be sure that these differences are not the products of a historical pattern of societal and labor market discrimination? Another way of posing the question is "how do we know when the work and career choices of women are subject to the same constraints as those faced by men?"

Even without specifying exactly what constitutes unacceptable gender distinctions in a labor market, we can examine the major competing theories advanced by economists to account for gender differences in wages. The major theories of labor market discrimination are 1) taste driven preferences, 2) market power, and 3) statistical discrimination. Below I take up each of these competing theories but note here that they are not mutually exclusive.

1. Theories of discrimination

1.1. Tastes and preferences

I begin with the tastes and preferences theory of labor market discrimination. This theory was first articulated in the path breaking work of Nobel Laureate Gary Becker (1957). In this work Becker employed the common monetary yard stick of the economist to measure discrimination. In arguably the best tradition of economics, Becker has labor market discrimination arising from utility maximization. In the Becker framework agents have "tastes" for discrimination with respect to groups of workers identified according to observable demographic traits such as race, ethnicity, and sex. These tastes are purely based on preferences and are distinctly different from attitudes generated from ignorance. Presumably, the latter would disappear in the face of information. The tastes to which Becker refers are immune to the facts. These preferences are akin to why some people prefer one color over another. They are simply embedded in one's utility function or preference ordering.

In the Becker framework employers, workers, consumers, and even governments have tastes for discrimination. It is easiest to consider separately these sources of discrimination, though all of these could be operating simultaneously. The operative concept in the Becker framework is the notion of a discrimination coefficient. The discrimination coefficient measures the degree to which an agent is willing to forfeit income in order to avoid certain types of economic interactions with individuals who belong to a particular demographic group.

First consider employer discrimination. An employer with a taste for discrimination acts as if the net wage of employing a worker from the discriminated against group is higher than the nominal wage. So for example, if an employer has a taste for discrimination against the employment of women in some occupation, this employer would act as if the wage cost of hiring a woman exceeds the nominal wage. Suppose an employer has a discrimination coefficient $d_e = 0.15$ and the nominal female wage is USD 20/hr. The employer would regard the net wage cost as $(1 + d_e)$ x USD 20 = (1.15) x USD 20 = USD 23/hr. The net wage cost increase of USD 3.00/hr is the psychic cost of employing a woman in the given occupation or job. What this means is that the employer would prefer hiring an equally qualified worker if the male wage were less than USD 23/hr. So if the male wage were USD 20, the employer would prefer hiring a man. Another way of looking at this is to note that the employer would be indifferent between hiring a man and a woman if the female wage fell to about USD 20/1.15 ≈ USD 17.39. This lower wage implies a 15 percent gender wage gap between equally qualified men and women. Becker analyzed the effects of increases in the relative labor supply of the discriminated against group in a market characterized by heterogeneity in employer tastes for discrimination. He also considered how the competitive conditions in an industry would affect labor market discrimination by employers. These considerations include cost conditions and in the case of monopoly, whether the monopoly is transferable or non transferable.

I now turn to discrimination by other economic agents, starting with discrimination by fellow workers. It will be assumed that neither employers nor consumers have tastes for discrimination. In the Becker framework, a worker with tastes for discrimination acts as if the net wage is lower than the nominal wage when working with members of a demographic group whom the worker would prefer to avoid. Suppose male workers have a discrimination coefficient d_w = 0.10 with respect to working with women in some particular job or occupation. If the nominal wage is USD 20/hr, the males will act as if the net wage were (1- d_w) x USD 20 = 0.9 x USD 20 = USD 18/hr. The difference of USD 2.00/hr measures the psychic cost of having to work with women in the particular job or occupation. Interestingly, the prediction in this case is that there would be no wage discrimination but only employment segregation. This is because the firm would have to pay the male workers a wage of USD 20/0.9 ≈ USD 22.22/hr to make them indifferent to working with women. How would the employer finance this extra wage cost? It might seem that it could be financed by offering women a lower wage. However, in a competitive labor market with no discrimination by either employers or consumers, women would chose to avoid employment in situations in which male workers' tastes for discrimination are present. Consequently, profit maximizing employers would not combine men and women in the same jobs or occupations. In other words, segregation arises but not wage discrimination. An interesting paper by Baldwin et al. (2001) examines a type of worker discrimination in which distaste by males for supervision by females leads to the presence of relatively fewer women as one ascends the managerial hierarchy of an organization.

In the case of consumer discrimination, a consumer with tastes for discrimination against women acts as if the net price of a product or service purchased from a woman is higher than the nominal (sticker) price. Suppose consumers have a discrimination coefficient $d_c = 0.15$. If the nominal price of the product were P = USD 115, the perceived net price of the product when sold by a woman would be $(1+ d_c)$ x USD 115 = 1.15 x USD 115 = USD 132.25. This implies that such a consumer would be indifferent between paying a male USD 132.25 for the product and paying a female USD 115 for the same product. The difference between the perceived net price and the nominal price is USD 132.25 - USD 115.00 = USD 17.25 and represents the psychic cost of purchasing the product from a woman rather than from a man.

How could consumer tastes lead to a gender wage gap between equally qualified men and women in an otherwise competitive environment? Here I assume that employers and workers have no tastes for discrimination. If the nominal price of the product were USD 115, how low would the price of the product have to be when sold by a woman (P_f) in order for a consumer to be indifferent between buying from men and women? The answer is $P_f = P/(1+d_c)$ = USD 115/1.15 = USD 100.

This means that the price has to be discounted in order to get consumers to purchase the product from women. From the perspective of a profit maximizing employer, the wage paid to workers has to match the value of their contribution. The standard condition is that $w = MP_L$ x P, where MP_L is the marginal product of labor. In this example it is assumed that men and women are equally productive and that their marginal products equal 0.1. In the case of males, this condition would yield $w_m = MP_L$ x P = (0.1)(USD115) = USD 11.50. However in the case of females $w_f = MP_L$ x P_f (0.1)(USD100) = USD 10.00. Here the gender wage gap is USD 1.50, or 15 percent in relative terms. Such a gap could easily arise in a case where sales workers are paid on commission. Female sales workers generate lower sales revenue because they are forced to discount their prices which in turn leads to lower commissions. The above example is equivalent to assuming a 10 percent sales commission for both men and women. From the employer viewpoint the commission formula is gender blind, yet because of consumer discrimination the outcome is biased against women.

When the average person thinks about labor market discrimination, it is probably the case that he or she has in mind discrimination by employers. In actuality the employer is unlikely to be the only source of discrimination or in some cases even the major source of discrimination. Anti-discrimination laws focus on employers but not necessarily because lawmakers believe that employers are the only or even the major source of discrimination. It is simply not very practical to enforce anti-discrimination laws against consumers and fellow workers. How can consumers be threatened with fines for not purchasing products or services provided by members of demographic groups against whom they have tastes for discrimination? As for worker discrimination perhaps the only legal leverage would be against trade unions that discriminated against members of certain demographic groups.

1.2. Market power

Despite the intuitive appeal of discriminatory preferences of economic agents as an explanation of labor market discrimination against women, other features of an economy can produce discriminatory gender wage gaps as well. Consider the case of labor market monopsony in which the labor market is dominated by a single employer. It pays this employer to hire less labor and offer a lower wage than would be the case in a competitive labor market. The idea is that the supply curve of labor to such an employer is actually the upward sloping labor supply curve to the market. In order to hire more labor, the employer must not only raise the wage of the last unit of labor employed but must also raise the wages of all previously hired units of labor. This is the case as long as the employer cannot make separate wage bargains with each individual unit of labor employed. The consequence is that the incremental cost of an additional unit of labor exceeds the higher wage paid to that last unit of labor. This is because the incremental cost includes the increased labor costs associated with raising the wages of all previous units of labor. A profit maximizing employer will want to hire labor up to the point where the incremental cost of hiring that last unit of labor just matches the incremental value (revenue) of that last unit. Because the higher wage needed to attract that last unit of labor is less than the incremental cost of the last unit, the wage actually paid falls short of the incremental value of the last unit of labor. This gap is referred to as "monopsonistic exploitation". Monopsonistic exploitation is a technical term that refers to the wedge between what labor is paid at the margin and what it produces in value. The Pigouvian exploitation index is measured as the proportionate difference between the marginal revenue product of workers and the actual wage. This type of exploitation does not necessarily have anything to do with worker dissatisfaction over their compensation.

An early example of discrimination arising from a noncompetitive labor market is found in Robinson (1933). In her classic book on imperfect competition, Joan Robinson considered the case of a single-employer labor market in which the elasticity of female labor supply to the market (in this case a single employer) is less than that of the labor supply of males. The scenario considered is one in which men and women are equally productive (perfect substitutes in production). Profit maximization requires that the employer hire men and women up to the point at which their marginal labor costs are equal to one another and to the marginal revenue product (incremental value) of labor. Because of the particular gender differences in labor supply elasticities assumed in this case, the wages offered to men will exceed those offered to women. The result is a gender wage gap that is not the result of productivity differences nor the result of tastes for discrimination. Rather, the gap reflects an opportunity for the monopsonistic employer to earn higher profits by taking advantage of the different labor supply elasticities for men and women.

Although the Robinson case was interesting and novel, it never established itself as a serious explanation for gender wage gaps. There are two reasons for its failure to be accepted as an important factor in accounting for gender wage gaps. The first is that typically the labor supply of males to the labor market is considered to be less elastic than that of females. Women have a non market alternative that is generally not present for men. Therefore among working age men, labor supply as measured by labor force participation is fairly inelastic. At first blush this would imply that men would generally be paid less than women. Since this is clearly not the case, it must be that the general labor market is reasonably competitive. Second, it is difficult to find many real world examples of local labor markets that are truly monopsonistic. Thus, the Robinson model would not be deemed to be empirically relevant.

A modern take on the monopsony idea can be found in Manning (2003) which draws on the search theoretic framework of Burdett and Mortensen (1998). Manning argues that labor market frictions can result in less than full information in a labor market because of search costs. Consequently, for any given employer, the labor supply curve may be upward sloping rather than appearing as a horizontal line to what otherwise would have been a (factor) price-taking firm in a competitive labor market. This means that despite a labor market characterized by competing employers, each individual employer has a degree of monopsony power. If female labor supply to a given employer is less elastic than that of males, the employer would find it profitable to pay lower wages to women who are equally qualified with men. Home responsibilities, the need to live closer to one's place of employment, and less mobility in general could all account for why female labor supply to a given firm may be less elastic than that of males.

Ransom and Oaxaca (2005) apply the Manning framework to data from an American company that lost a lawsuit over sex discrimination in promotions and wages. The key to identifying the labor supply elasticities faced by the company for males and females was in estimating the wage elasticity of job separation. In the Manning framework, under some fairly tight assumptions, a group's labor supply elasticity can be estimated as minus 2 times the estimated (negative) wage elasticity of job separations. The Pigouvian measure of exploitation can be shown to equal the reciprocal of the labor supply elasticity. In the case of the American company, the wage elasticity of job separation was smaller for women which directly implies that the labor supply elasticity of women is less than that of men. The predicted gender wage differential can be shown to be simply the gender difference in the exploitation measure. As it turned out, the predicted gender wage gap from monopsony power was very close to the conventionally estimated gender wage differential in this case. At least from this example, it appears that most of the discriminatory wage gap can be accounted for by the presence of monopsony power.

1.3. Statistical discrimination

A third major theory of discrimination involves "profiling" which refers to singling individuals out for special scrutiny on the basis of their demographic characteristics. In other words, individuals are judged on the basis of group characteristics rather than individual merit. The pioneering work on this topic may be found in Arrow (1971), Phelps (1972), and Aigner and Cain (1977). Statistical discrimination can be either of the first moment variety or of the second moment variety. In a labor context I will consider two groups of workers identified by demographic characteristics. Let's say that these two groups are men and women. For statistical discrimination of the first moment variety, suppose that men are believed by employers to be more productive on average than women. Even if this assumption were true, it is possible that in any given case a female job applicant could be more productive than a competing male applicant. If the costs of determining which one of the job candidates is actually more productive are sufficiently high, the employer will use the worker's gender as a signal of productivity. In this case the job would be offered to the male candidate if the wages were the same. To be indifferent between hiring the male applicant and the female applicant, the employer would have to be faced with the prospect of offering a lower wage to the female job applicant.

The second moment variety of statistical discrimination has to do with group distinctions based on actual or perceived differences in productivity risk or variance. Here again I will consider men and women. Suppose that on average men and women are equally productive in the job market. However, suppose that employers believe that the productivity distribution for female workers is more variable, e.g. childbirth and a higher leave of absence for child care. Again gender becomes a signal if the cost of attempting to learn which job applicant will be more productive is sufficiently high. In order for a risk averse employer to be indifferent between hiring a female job applicant and a male job applicant, the employer would have to be faced with offering a lower wage to the female job applicant. The wage differential serves as compensation for the perceived risk. Of course a risk neutral employer would be indifferent between hiring a male and a female if their expected productivities are believed to be the same. Dickinson and Oaxaca (2006) reports the findings of laboratory experiments that explore aspects of statistical discrimination of the second moment variety. The results suggest that increased risk associated with productivity distributions generates lower wage contracts for workers.

One can find many examples of statistical discrimination outside of the labor market context. One that comes to mind is gender differences in automobile insurance premiums. It is a common feature in the US that young men face higher auto insurance premiums than young women. The reason is that the actuarial experience with auto accidents and the value of insurance claims are less favorable for young men on average. Given that it is difficult for an insurance company to know ex-ante what the driving record will be of a young auto insurance applicant, gender is used as a signal. Thus far this practice is legal in the US. Another example has to do with pension payments. In the US and many other countries, women outlive men. To equate the expected present value of pensions for a male and a female who retire at the same age, it would be necessary to make smaller periodic payments to women. While this would appear to be as actuarially sound as the case with auto insurance premiums, this practice is illegal in the US (Arizona Governing Committee v. Morris, 82-52, US Supreme Court, July 6, 1983). Generally, gender wage gaps arising from statistical discrimination in the labor market would be illegal as well. In the labor market context, however, the "actuarial" evidence is far from being as clear cut as in the auto insurance or pension cases.

2. Measurement of labor market discrimination

A conceptually straight forward approach to the measurement of labor market discrimination is found in the decomposition method described in Blinder (1973) and Oaxaca (1973). The basic idea is that in a nondiscriminating environment, men and women should be compensated according to the same compensation formula. While in some human capital settings this basic assertion might be challenged, for the time being I will accept this definition of labor market equity in wage determination.

2.1. Basic wage decompositions

In the real world it is not very often that the researcher can directly observe the wage determination process at the level of the individual. Hence the wage determination process is modeled as a stochastic process. I will follow the convention in labor economics and work in terms of the natural logarithm of wages:

$$Y_{mi} = X'_{mi}\beta_m + \varepsilon_{mi}, i = 1,...N_m \tag{1}$$

$$Y_{fi} = X'_{fi}\beta_f + \varepsilon_{fi},\ i = 1,...N_f, \tag{2}$$

where m and f refer to males and females, respectively, i indexes the individual worker, Y is the natural logarithm of the wage, X^* is a vector of individual wage determining characteristics, β is a vector of coefficients, ε is a random error term, and N denotes sample size. The standard classical statistical assumptions require that the means of the error terms be equal to zero so that on average individuals would receive $X_i'\beta$ as compensation (in terms of logs).

Belief that gender equity requires that $\beta_m = \beta_f$, suggests a way of determining statistically how much of the observed average wage gap between men and women can be attributed to discrimination. First, one would statistically estimate the wage determination equations separately for men and women. Given the classical assumptions, ordinary least squares (*OLS*) would be the estimator of choice. When evaluated at the sample means, the estimated models have the property that the regression hyperplane passes through the sample means: $\overline{Y}_m = \overline{X}_m'\hat{\beta}_m$ and $\overline{Y}_f = \overline{X}_f'\hat{\beta}_f$, where $\overline{Y}$ is the sample mean (log) wage, $\overline{X}'$ is the sample mean vector for the explanatory variables, and $\hat{\beta}$ is the estimated vector of coefficients. In the absence of discrimination, the expected values of the estimated coefficients should be equal for men and women, $E(\hat{\beta}_m) = E(\hat{\beta}_f)$. Thus, on average the only wage differences that should arise between men and women should be the result of gender differences in wage determining characteristics (the $\overline{X}'$ vectors). Hence, it is important to determine how much of the average gender wage gap $\left(\overline{Y}_m - \overline{Y}_f\right)$ arises from the difference in characteristics (endowments or qualifications), and how much arises from the parameter gap $\left(\hat{\beta}_m - \hat{\beta}_f\right)$. It is the contribution of the parameter gap that is often taken to be the measure of discrimination.

There are any number of ways to decompose the gender wage gap $\left(\overline{Y}_m - \overline{Y}_f\right)$ into components arising from $\left(\overline{X}_m' - \overline{X}_f'\right)$ and $\left(\hat{\beta}_m - \hat{\beta}_f\right)$. The researcher needs to make some assumption about the nondiscriminatory norm that should apply equally to men and women. A very common assumption is to adopt the estimated male wage structure $\left(\hat{\beta}_m\right)$ as the non discriminatory norm. This assumption stems from the fact that male workers are usually the dominant group. So the focus on gender equity is to treat female workers like their male counterparts rather than vice-versa. In this case a little algebra shows that the wage gap can be expressed as

$$\overline{Y}_m - \overline{Y}_f = \left(\overline{X}'_m - \overline{X}'_f\right)\hat{\beta}_m + \overline{X}'_f\left(\hat{\beta}_m - \hat{\beta}_f\right). \quad (3)$$

In equation (3) the first term $\left(\overline{X}'_m - \overline{X}'_f\right)\hat{\beta}_m$ represents how much of the gap arises because men and women differ on average in their wage determining characteristics. In other words this component measures the wage gap that would exist if men and women were both compensated according to the wage determination process for men. This is sometimes referred to as "explained" gap. The second term in (3) is $\overline{X}'_f\left(\hat{\beta}_m - \hat{\beta}_f\right)$ and is often interpreted as an estimate of labor market discrimination. This is because this term measures how much of the gap is accounted for by the fact that men and women do not face the same wage determination process, $\hat{\beta}_m \neq \hat{\beta}_f$. This gap is actually a residual because it is what is left over after subtracting $\left(\overline{X}'_m - \overline{X}'_f\right)\hat{\beta}_m$ from $\left(\overline{Y}_m - \overline{Y}_f\right)$. Indeed, this gap can be calculated without ever having to estimate $\hat{\beta}_f$ separately for the female sample. Oaxaca (1973) interprets this gap as the Becker discrimination coefficient (in logs).

In contrast to the discrimination characterization, some prefer to label the term $\overline{X}'_f\left(\hat{\beta}_m - \hat{\beta}_f\right)$ as the "unexplained" gap. The reasoning behind using this terminology rather than discrimination is that there is a fear that variables may have been omitted from the model that bias the results. Of course there is no necessary presumption about what the direction of bias would be (see Oaxaca and Ransom, 2003). It is possible that the omitted variables lead to an underestimate of discrimination rather than to an overestimate. While this can be a valid concern, there are some philosophical or possibly ideological factors at work. This type of decomposition method has been applied in many other contexts, e.g. public vs. private sector wage differentials, union vs. nonunion wage differentials, manufacturing vs. nonmanufacturing differentials. In none of these cases are these differentials labeled "unexplained". To do so would be confusing indeed, especially if the differentials were estimated simultaneously by sets of dummy indicator variables in a single wage regression model. As for likely misspecification of the wage model, the wage equations follow standard specifications used by economists. So the question becomes one of why the wage model suddenly become misspecified when we learn that it will be used to decompose the gender wage gap.

Even if one were inclined to accept the unexplained gap as an estimate of discrimination, one might wonder how much of the discrimination term reflects favoritism toward males versus pure discrimination against females. Using either the estimated male coefficients or the estimated female coefficients as the nondiscriminatory norm, constitutes a very special case. Adopting the estimated male wage coefficients as the standard implies that men on average are compensated appropriately but that the problem is that women are undercompensated. On the other hand adopting the estimated female coefficients as the standard implies that on average women are appropriately compensated but the problem is that men are overcompensated.

In Neumark (1988) and Oaxaca and Ransom (1988, 1994) a generalized decomposition methodology is developed that can identify how much of the gap is due to favoritism and how much is pure discrimination. The idea is to find a nondiscriminatory wage structure that is not necessarily identical to that of either group. The decomposition would be expressed as

$$\overline{Y}_m - \overline{Y}_f = \left(\overline{X}_m' - \overline{X}_f'\right)\hat{\beta}^* + \overline{X}_m'\left(\hat{\beta}_m - \hat{\beta}^*\right) + \overline{X}_f'\left(\hat{\beta}^* - \hat{\beta}_f\right), \tag{4}$$

where $\hat{\beta}^*$ is an estimate of a nondiscriminatory norm that is not necessarily identical to either $\hat{\beta}_m$ or $\hat{\beta}_f$. The first term in (4), $\left(\overline{X}_m' - \overline{X}_f'\right)\hat{\beta}^*$, estimates how much of the wage gap would exist just based on gender differences in qualifications; the second term, $\overline{X}_m'\left(\hat{\beta}_m - \hat{\beta}^*\right)$, estimates how much of the wage gap is attributable to favoritism toward men; and the third term, $\overline{X}_f'\left(\hat{\beta}^* - \hat{\beta}_f\right)$, estimates how much of the wage gap is attributable to pure discrimination against women. Total discrimination is estimated as the sum of the favoritism and pure discrimination terms. One can relate $\hat{\beta}^*$ to $\hat{\beta}_m$ and $\hat{\beta}_f$ via the arbitrary matrix weighted average expression $\hat{\beta}^* = \Omega\hat{\beta}_m + (I - \Omega)\hat{\beta}_f$. While there is potentially an infinite number of ways to obtain $\hat{\beta}^*$, special cases that have been typically considered arise as follows: $\hat{\beta}^* = \hat{\beta}_m$ for $\Omega = I$; $\hat{\beta}^* = \hat{\beta}_f$ for $\Omega = 0$; and $\hat{\beta}^* = 0.5(\hat{\beta}_m + \hat{\beta}_f)$ for $\Omega = 0.5I$. An particularly appealing estimated non discriminatory wage structure is one in which $\Omega = (X_m' X_m + X_f' X_f)^{-1} X_m' X_m$. This weighting scheme obtains $\hat{\beta}^*$ as a common parameter vector estimated from the pooled male and female samples. The weights are determined by the amount of sample variation in the *X's* for men and women. For a discussion of how to obtain estimated standard errors on wage decomposition components see Oaxaca and Ransom (1998). Jann (2005) also provides a module in STATA to compute wage decomposition components and their associated standard errors.

A simple indicator variable approach for estimating discrimination is also commonly found in the literature. Consider the following wage determination model for a pooled sample of male and female workers:

$$Y_i = \beta_o + \underline{X}_i' \underline{\beta} - \delta F_i + \varepsilon_i, \; i = 1, \ldots N_m + N_f$$

where β_o is the constant term, $\underline{X}'$ is a vector of the wage determination variables other than the constant term, $\underline{\beta}$ is the vector of coefficients, F is an indicator variable that assumes the value 1 if the worker is a female and 0 otherwise, and δ is a coefficient. If the model is estimated by *OLS*, the mean (log) wages for males and females are given by $\overline{Y}_m = \hat{\beta}_o + \overline{\underline{X}}_m' \hat{\underline{\beta}}$ and $\overline{Y}_f = \hat{\beta}_o + \overline{\underline{X}}_f' \hat{\underline{\beta}}$. The resulting wage decomposition is

$$\overline{Y}_m - \overline{Y}_f = \left(\overline{\underline{X}}_m' - \overline{\underline{X}}_f'\right) \hat{\underline{\beta}} + \hat{\delta}. \qquad (5)$$

It is clear that the first term in (5), $\left(\overline{\underline{X}}_m' - \overline{\underline{X}}_f'\right) \hat{\underline{\beta}}$, is the explained portion of the gap and represents the magnitude of the gap if the coefficients on the wage determination characteristics were constrained to be the same for men and women. The second term in (5), $\hat{\delta}$, is an estimate of discrimination/unexplained gap.

The major difference among the alternative decomposition approaches discussed above is what estimated parameter vector is being used when male and females are constrained to face the same wage structure, i.e., $\hat{\beta}_m$, $\hat{\beta}_f, \hat{\beta}^*$, or $\left(\hat{\beta}_o, \underline{\hat{\beta}}\right)$. Clearly, one's inferences about the extent of discrimination will be affected by which method is used since in general these will not yield identical decomposition components. It could be argued that one's choice of decomposition method and the selection of which variables to include in the list of explanatory variables operationally defines what one means by discrimination. For example if one included indicator variables for type of job or occupation of the worker, then gender differences in occupations might be thought to be voluntary so that discrimination is confined to gender wage gaps within occupations. On the other hand, one might chose to omit the controls for occupation if one believes that gender differences in occupational affiliation result from labor market discrimination. The problem is that in aggregate labor markets it is difficult to identify how much of the gender difference in occupational distribution reflects discriminatory labor market constraints and how much of the gap reflects differences in career preferences.

2.2. Residual wage decompositions

In the spirit of explaining changes in the unexplained wage gap, Juhn, Murphy and Pierce (1991) (hereafter referred to as JMP) constructs a decomposition that seeks to account for changes in the unobserved prices and quantities that comprise the change in the unexplained wage gap over some time period. The wage equation for a typical worker in period t would be written as $Y_{it} = X_{it}'\beta_t + \sigma_{\varepsilon t} v_{it}$, where $\sigma_{\varepsilon t} v_{it} = \varepsilon_{it}$ and v_{it} is a standardized residual with mean 0 and variance 1. Assuming the male wage structure as the norm, the JMP decomposition applied to gender wage gaps yields the expression

$$\Delta\overline{Y}_t = \Delta\overline{X}_t'\hat{\beta}_{mt} + \hat{\sigma}_{\varepsilon mt}\Delta\hat{v}_t ,$$

where

$$\Delta\overline{Y}_t = \overline{Y}_{mt} - \overline{Y}_{ft},\ \Delta\overline{X}_t' = \left(\overline{X}_{mt}' - \overline{X}_{ft}'\right), \text{ and } \hat{\sigma}_{\varepsilon mt}\Delta\hat{v}_t$$

represents the gender difference in standardized residuals (unobserved components). Because the mean residuals for men and women are constrained to equal 0 in the *OLS* case, $\Delta\hat{v}_t$ cannot be the literal difference in mean residuals between men and women. It is easily seen that $\hat{\sigma}_{\varepsilon mt}\Delta\hat{v}_t = \overline{X}'_{ft}\left(\hat{\beta}_{mt} - \hat{\beta}_{ft}\right)$, which brings us back to the unexplained (discriminatory?) wage gap. The original intent of JMP was to decompose wage gap changes over time into changes in observable prices $\left(\hat{\beta}_t\right)$ and quantities $\left(\Delta\overline{X}_t\right)$ and changes in unobservable prices $\left(\hat{\sigma}_{\varepsilon t}\right)$ and quantities $\left(\Delta\hat{v}_t\right)$.

If we wish to decompose changes in the gender wage gap between period *t* and period t_0, the JMP decomposition could be expressed as

$$\begin{aligned}\Delta\overline{Y}_t - \Delta\overline{Y}_{t_0} &= \left(\Delta\overline{X}'_t - \Delta\overline{X}'_{t_0}\right)\hat{\beta}_{mt_0} + \Delta\overline{X}'_t\left(\hat{\beta}_{mt} - \hat{\beta}_{mt_0}\right) \\ &\quad + \left(\Delta\hat{v}_t - \Delta\hat{v}_{t_0}\right)\hat{\sigma}_{\varepsilon mt_0} + \Delta\hat{v}_t\left(\hat{\sigma}_{\varepsilon mt} - \hat{\sigma}_{\varepsilon mt_0}\right).\end{aligned} \tag{6}$$

The first two terms in (6) correspond to the effects of changes in observed productivity differences between men and women and the effects of changes in the observed male returns to productivity characteristics. The last two terms in (6) correspond to the effects of changes in unobserved wage determining effects and changes in the prices of unobserved wage determining effects. However, the sum of these last two terms is simply the estimated change in the unexplained or discriminatory gap, depending on how one wishes to characterize the residual gap.

Suen (1997) offers a critique of the JMP decomposition in terms of identifying the effects of changes in unobserved productivity (a ranking effect in the wage distribution) and the effects of changes in unobserved prices (the variance of the wage distribution). Basically, the idea is that it is not plausible to assume that the rankings in residual wage distributions are independent of the residual wage distribution variance.

In the Datta Gupta et al. (2006) comparative study of the relative progress of women in the Danish and US labor markets, the JMP decomposition is used but it is explicitly related to the generalized decomposition of Oaxaca and Ransom (1994). Given that the regression model is pooled over the combined sample of men and women, the mean residuals for each group are not identically equal to zero. This means that $\hat{\sigma}_{\varepsilon t}\overline{v}_{mt} = \overline{X}'_{mt}\left(\hat{\beta}_{mt} - \hat{\beta}^*_t\right)$ and $\hat{\sigma}_{\varepsilon t}\overline{v}_{ft} = -\overline{X}'_{ft}\left(\hat{\beta}^*_t - \hat{\beta}_{ft}\right)$ so that

$$\hat{\sigma}_{\varepsilon t}\Delta\bar{v}_t = \hat{\sigma}_{\varepsilon t}\bar{v}_{mt} - \hat{\sigma}_{\varepsilon t}\bar{v}_{ft}$$
$$= \overline{X}'_{mt}\left(\hat{\beta}_{mt} - \hat{\beta}^*_t\right) + \overline{X}'_{ft}\left(\hat{\beta}^*_t - \hat{\beta}_{ft}\right).$$

Decomposition of the changes in $\hat{\sigma}_{\varepsilon t}\Delta\bar{v}_t$ over time can be interpreted via the JMP story or alternatively in terms of changes in discrimination that are related to changes in $\hat{\beta}_{mt}, \hat{\beta}_{ft}$, and $\hat{\beta}^*_t$.

2.3. Identification issues

Assume for the moment that one is satisfied with a particular decomposition approach and with a particular list of explanatory wage determining variables. Beyond estimating how much of the gender wage gap can be assigned to gender differences in productivity characteristics and how much remains as a candidate for discrimination, a researcher might wish to know how much each wage determining variable contributes to each of the two components of the wage gap. Jones (1983) demonstrated the existence of an identification problem when one attempts to further disaggregate the components of the decomposition. A simple example will illustrate the issues involved. Let us suppose that wages in some setting are determined by whether or not the worker is a university graduate and the number of years of work experience. The simple wage determining formulas for men and women may be expressed as

$$Y_{mi} = \beta_{0m} + \beta_{1m}G_{mi} + \beta_{2m}T_{mi} + \varepsilon_{mi}, i = 1,...N_m$$
$$Y_{fi} = \beta_{0f} + \beta_{1f}G_{fi} + \beta_{2f}T_{fi} + \varepsilon_{fi}, i = 1,...N_f$$

where G is an indicator variable that takes the value of 1 if the worker is a university graduate and 0 otherwise, and T is years of work experience. Consider the case in which the male wage structure is considered the nondiscriminatory norm. The empirical wage decomposition would be expressed as

$$\overline{Y}_m - \overline{Y}_f = \left(\overline{G}_m - \overline{G}_f\right)\hat{\beta}_{1m} + \left(\overline{T}_m - \overline{T}_f\right)\hat{\beta}_{2m}$$
$$+ \left(\hat{\beta}_{0m} - \hat{\beta}_{0f}\right) + \left(\hat{\beta}_{1m} - \hat{\beta}_{1f}\right)\overline{G}_f + \left(\hat{\beta}_{2m} - \hat{\beta}_{2f}\right)\overline{T}_f,$$

where $\overline{G}_m$ and $\overline{G}_f$ are the sample proportions of males and females who are university graduates, and $\overline{T}_m$ and $\overline{T}_f$ are the sample mean work experiences for males and females. As before, the effect of gender differences in characteristics is captured by $\left(\overline{G}_m - \overline{G}_f\right)\hat{\beta}_{1m} + \left(\overline{T}_m - \overline{T}_f\right)\hat{\beta}_{2m}$ and the effect of discrimination is captured by $\left(\hat{\beta}_{0m} - \hat{\beta}_{0f}\right) + \left(\hat{\beta}_{1m} - \hat{\beta}_{1f}\right)\overline{G}_f + \left(\hat{\beta}_{2m} - \hat{\beta}_{2f}\right)\overline{T}_f$.

If we wanted to determine how much gender differences in educational attainment contribute to the wage gap, we would simply use $\left(\overline{G}_m - \overline{G}_f\right)\hat{\beta}_{1m}$ as our measure. Similarly, if we wished to estimate how much gender differences in work experience contributed to the wage gap we would use $\left(\overline{T}_m - \overline{T}_f\right)\hat{\beta}_{2m}$. If we were interested in knowing how much gender inequity in the returns to work experience contributes to the wage gap, we would simply calculate $\left(\hat{\beta}_{2m} - \hat{\beta}_{2f}\right)\overline{T}_f$. Now suppose we wish to determine how much of the wage gap can be attributed to gender differences in the returns to education. It would seem that one need only use $\left(\hat{\beta}_{1m} - \hat{\beta}_{1f}\right)\overline{G}_f$ as our measure. However, suppose we had decided to define the education variable as an indicator that takes on the value 1 if the worker is *not* a university graduate and 0 otherwise. This means that the left out educational reference group is university graduate rather than non university graduate. If we let S be an indicator variable for non university graduate, it is clear that $S = 1 - G$. The wage model specification becomes

$$
\begin{aligned}
Y_{mi} &= \theta_{0m} + \theta_{1m}S_{mi} + \beta_{2m}T_{mi} + \varepsilon_{mi}, i = 1,...N_m \\
Y_{fi} &= \theta_{0f} + \theta_{1f}S_{fi} + \beta_{2f}T_{fi} + \varepsilon_{fi}, i = 1,...N_f
\end{aligned}
$$

The fundamental regression is unchanged by substitution of a different left out reference group for education. One can show that $\theta_0 = \beta_0 + \beta_1$ and $\theta_1 = -\beta_1$. How does this substitution affect the decomposition? The decomposition would now be expressed as

$$
\begin{aligned}
\overline{Y}_m - \overline{Y}_f = &\left(\overline{S}_m - \overline{S}_f\right)\hat{\theta}_{1m} + \left(\overline{T}_m - \overline{T}_f\right)\hat{\beta}_{2m} \\
&+ \left(\hat{\theta}_{0m} - \hat{\theta}_{0f}\right) + \left(\hat{\theta}_{1m} - \hat{\theta}_{1f}\right)\overline{S}_f + \left(\hat{\beta}_{2m} - \hat{\beta}_{2f}\right)\overline{T}_f.
\end{aligned}
$$

It can be shown (Oaxaca and Ransom, 1999) that the overall decomposition is unchanged by the substitution of left out reference groups so that

$$\left(\overline{S}_m - \overline{S}_f\right)\hat{\theta}_{1m} + \left(\overline{T}_m - \overline{T}_f\right)\hat{\beta}_{2m} = \left(\overline{G}_m - \overline{G}_f\right)\hat{\beta}_{1m} + \left(\overline{T}_m - \overline{T}_f\right)\hat{\beta}_{2m} \tag{7}$$

and

$$\begin{aligned}&\left(\hat{\theta}_{om} - \hat{\theta}_{of}\right) + \left(\hat{\theta}_{1m} - \hat{\theta}_{1f}\right)\overline{S}_f + \left(\hat{\beta}_{2m} - \hat{\beta}_{2f}\right)\overline{T}_f = \\ &\left(\hat{\beta}_{0m} - \hat{\beta}_{0f}\right) + \left(\hat{\beta}_{1m} - \hat{\beta}_{1f}\right)\overline{G}_f + \left(\hat{\beta}_{2m} - \hat{\beta}_{2f}\right)\overline{T}_f.\end{aligned} \tag{8}$$

Are the subcomponents of the decomposition also invariant to the substitution? Since the term $\left(\overline{T}_m - \overline{T}_f\right)\hat{\beta}_{2m}$ does not change and the total endowment effect is unchanged, it is necessarily the case that $\left(\overline{S}_m - \overline{S}_f\right)\hat{\theta}_{1m} = \left(\overline{G}_m - \overline{G}_f\right)\hat{\beta}_{1m}$. Thus we would say that the contribution of gender differences in the individual wage determinants are identified. What about the contribution of gender differences in estimated coefficients for individual variables? It is clear that the term $\left(\hat{\beta}_{2m} - \hat{\beta}_{2f}\right)\overline{T}_f$ is unaffected by the substitution. However, it is easily shown that

$$\begin{aligned}\left(\hat{\theta}_{0m} - \hat{\theta}_{0f}\right) &= \left(\hat{\beta}_{0m} - \hat{\beta}_{0f}\right) + \left(\hat{\beta}_{1m} - \hat{\beta}_{1f}\right) \\ &\neq \left(\hat{\beta}_{0m} - \hat{\beta}_{0f}\right).\end{aligned}$$

The result is that the contribution of gender differences in the constant term to measured discrimination is not invariant to the choice of left out reference group. Furthermore, this fact and the fact that $\left(\hat{\beta}_{2m} - \hat{\beta}_{2f}\right)\overline{T}_f$ is unchanged, coupled with the fact that the overall discrimination component is unchanged, necessarily implies that $\left(\hat{\theta}_{1m} - \hat{\theta}_{1f}\right)\overline{S}_f \neq \left(\hat{\beta}_{1m} - \hat{\beta}_{1f}\right)\overline{G}_f$. This means that one cannot identify the effect of inequity in the returns to education because the measure is not invariant to the choice of left out reference group.

It might appear that the problem could be solved by simply combining the gender difference in constant terms with the gender difference in estimated returns to education. In this simple example, counting the difference in constant terms along with the differences in education effects would yield a sum that would indeed be invariant to the choice of left out reference group. This total could be identified as the schooling effect of gender inequity. Unfortunately, as shown in Oaxaca and Ransom (1999) the problem returns when there is more than one set of variables defined by sets of indicator variables. Thus for example if one were to add an indicator variable for marital status, the identification problem would return. Note that in the case of estimating discrimination as the coefficient on a gender dummy variable, equation (5), the identification problem does not arise because the estimate of discrimination is captured by a single parameter $\hat{\delta}$ that is not subject to further disaggregation.

A number of papers have appeared in the literature that attempt to address the identification issue, Nielsen (2000), Gardeazabal and Ugidos (2004), and Yun (2005). A particularly simple solution to the identification problem is to normalize the coefficients on sets of indicator variables so that the coefficients sum to zero, see Gardeazabal and Ugidos (2004) and Yun (2005). This solution can be illustrated using the example above. Suppose the wage equation for a group of workers is written as

$$\begin{aligned} Y_i &= b_0 + b_1 G_i + c_1 S_i + \beta_2 T_i + \varepsilon_i \\ &= b_0 + b_1 \left(G_i - S_i\right) + \beta_2 T_i + \varepsilon_i \end{aligned}$$

since $b_1 + c_1 = 0$, so that $c_1 = -b_1$. This normalization does not affect the fundamental regression model but it does offer a way to finesse the decomposition identification problem. After a little algebra, the decomposition can be expressed as

$$\begin{aligned} \overline{Y}_m - \overline{Y}_f &= \left[\left(\overline{G}_m - \overline{G}_f\right) - \left(\overline{S}_m - \overline{S}_f\right)\right]\hat{b}_{1m} + \left(\overline{T}_m - \overline{T}_f\right)\hat{\beta}_{2m} \\ &+ \left(\hat{b}_{0m} - \hat{b}_{0f}\right) + \left(\overline{G}_f - \overline{S}_f\right)\left(\hat{b}_{1m} - \hat{b}_{1f}\right) + \left(\hat{\beta}_{2m} - \hat{\beta}_{2f}\right)\overline{T}_f . \end{aligned}$$

It can be shown that the total endowment effect given by $\left[\left(\overline{G}_m - \overline{G}_f\right) - \left(\hat{S}_m - \hat{S}_f\right)\right]\hat{b}_{1m} + \left(\overline{T}_m - \overline{T}_f\right)\hat{\beta}_{2m}$ is identical to the total endowment effect obtained from the conventional decomposition given by (7). Similarly, the total discrimination effect is identical to that obtained from the conventional decomposition given by (8). What is different is that the contribution of gender differences in the estimated constant terms, $\left(\hat{b}_{0m} - \hat{b}_{0f}\right)$, and the gender difference in the estimated returns to education, $\left(\overline{G}_f - \overline{S}_f\right)\left(\hat{b}_{1m} - \hat{b}_{1f}\right)$, are not affected by the choice of the left out reference group. In particular, $\left(\overline{G}_f - \overline{S}_f\right)\left(\hat{b}_{1m} - \hat{b}_{1f}\right) = -\left(\overline{G}_f - \overline{S}_f\right)\left(\hat{c}_{1m} - \hat{c}_{1f}\right)$.

It should be borne in mind that identification of the contribution of individual variables to discrimination still requires some sort of normalization. Unless researchers adopt the same normalizations, detailed decomposition results would not be comparable across studies.

2.4. Sample selection

With the pioneering work of Nobel Laureate James Heckman (1976, 1979) economists became sensitive to the problem of working with samples that are subject to selection bias. Consider a sample of working women. If it turns out that unobserved factors that determine the propensity of a woman to work in the market sector are correlated with unobserved factors that determine the wages of working women, conventional *OLS* estimation of the wage equation can yield biased and inconsistent estimators of the wage equation coefficients. This is because the unobserved error term in the classical wage model includes a term that will depend on the variables that enter the decision to participate in the labor market. This omitted variable will likely be correlated with the wage determining variables.

The basic selection bias framework consists of two equations:

$$prob\left(E_i = 1\right) = prob(Z_i'\gamma + u_i \geq 0), i = 1,...N \tag{9}$$

and

$$Y_i = X_i'\beta + \varepsilon_i, i = 1,...N_e \tag{10}$$

where E is an indicator variable that takes on the value 1 if the individual is working in the market sector and 0 otherwise, Z' is a vector of observed variables that determine the probability that one would be working in the market sector, γ is a vector of coefficients, u is a random error term, N is the total sample size, and N_e is the subsample of individuals who are observed to be working ($N_e < N$). Generally, there would be some overlap in the variables comprising Z and X. Assume that the error terms in both equations are normally distributed and are correlated with one another. The wage equation is then more accurately expressed as a conditional equation (conditional on the fact that $E_i = 1$ for the subsample N_e:

$$\begin{aligned} Y_i \mid (E_i = 1) &= X_i'\beta + \varepsilon_i \mid (E_i = 1) \\ &= X_i'\beta + \varrho\sigma\lambda_i + \psi_i \end{aligned} \tag{11}$$

where ρ is the correlation between u and ε, σ is the standard deviation of ε, λ is a function of $Z'\gamma$ known as the Inverse Mills Ratio, and ψ is a mean zero error term. If one estimates equation (10) by *OLS*, this is equivalent to estimating (11) without the term $\rho\sigma\lambda_i$. This is what Heckman (1979) characterized as an omitted variables problem because λ would generally be correlated with X'. The consequence is that the *OLS* estimator of β would be biased and inconsistent. Heckman proposed a two-stage estimation procedure to first estimate γ from a probit model. Construct an estimate $\hat{\lambda}$ from $Z'\hat{\gamma}$, and then estimate the modified conditional wage equation by *OLS*:

$$Y_i \mid (E_i = 1) = X_i'\beta + \varrho\sigma\hat{\lambda}_i + \psi_i^*.$$

It is also possible to estimate the wage model in one step by maximum likelihood. In any event one would have consistent estimators of the model's parameters.

The question I wish to raise here is "how does correction for selectivity bias affect wage decompositions?" This is the question examined in Neuman and Oaxaca (2004). At the very least one can write the decomposition as

$$\begin{aligned} \overline{Y}_m - \overline{Y}_f &= \left(\overline{X}_m' - \overline{X}_f'\right)\hat{\beta}_m + \overline{X}_f'\left(\hat{\beta}_m - \hat{\beta}_f\right) \\ &\quad + \hat{\varrho}_m\hat{\sigma}_m\hat{\lambda}_m - \hat{\varrho}_f\hat{\sigma}_f\hat{\lambda}_f. \end{aligned} \tag{12}$$

The first two terms in (12) are the familiar endowment and discrimination terms. The last two terms in (12) reflect the contribution of gender differences in the selectivity terms to the overall wage gap. We can denote by $\hat{\lambda}_f^0$ the mean value of the Inverse Mills Ratio if women faced the same estimated γ that the men face. The problem is how to interpret the effects of the selectivity terms along the lines of explained and unexplained (discriminatory) components. Should gender differences in ρ, σ, and γ be interpreted as explained effects, unexplained or discriminatory effects?

In the Neuman and Oaxaca (2005) study of salary differentials among Israeli salaried professional workers, it is demonstrated that how one decomposes $\hat{\varrho}_m \hat{\sigma}_m \hat{\lambda}_m - \hat{\varrho}_f \hat{\sigma}_f \hat{\lambda}_f$ and assigns the component terms can make a major difference in the inferences one might draw about the extent of labor market discrimination. To illustrate, it is noted that among Israeli salaried professional workers, the unadjusted gender (log) wage gap among Westerners was 0.26. If the selection term $\hat{\varrho}_m \hat{\sigma}_m \hat{\lambda}_m - \hat{\varrho}_f \hat{\sigma}_f \hat{\lambda}_f$ is treated as a separate component in the wage decomposition, the estimated discriminatory wage gap is 0.17 or 65 percent of the raw wage gap. On the other hand if the selection term is decomposed so that $\hat{\varrho}_m \hat{\sigma}_m (\hat{\lambda}_m - \hat{\lambda}_f^0)$ (the effects of gender differences in the variables that determine the probability of being employed) is included in the explained portion of the wage gap, and $\hat{\varrho}_m \hat{\sigma}_m \hat{\lambda}_f^0 - \hat{\varrho}_f \hat{\sigma}_f \hat{\lambda}_f$ (the effects of gender differences in selection parameters) is assigned to the discriminatory portion of the wage gap, the estimated discriminatory gap falls to 0.10 or 38 percent of the gap.

2.4. Equity salary adjustments

Policy makers and private decision makers alike are presumably interested in measuring discrimination not only for the sake of documenting its absolute and relative importance, but also with an eye on how to correct documented inequities. Oaxaca and Ransom (2003) explores some of the issues that complicate the direct application of discrimination measures to the correction of gender salary inequities within a firm. The point of departure is where average wage discrimination against women has been determined on the basis of a wage decomposition model. The specification of the model has been determined as the result of a legal or some other dispute resolution process in which the parties have presented all of their arguments. Consequently, there is no question of specification bias in the estimated measure of discrimination. The problem posed here is how to allocate the estimated total amount of salary underpayment to women subject to the constraint that no individual's salary is reduced by the adjustment process. This constraint can be dictated by legal restrictions and concerns over employee morale. One might plausibly assume that the estimated salary model for males serves as the nondiscriminatory wage structure that will guide the salary adjustment process.

A straightforward and naive salary adjustment algorithm is to award each female worker the average estimated amount of salary discrimination, i.e. $\overline{X}_f'\left(\hat{\beta}_m - \hat{\beta}_f\right)$. Unfortunately, this method has the property that each female worker receives the same adjustment regardless of the degree to which she is underpaid. It is also a subtle form of gender discrimination against men because salary raises are given to workers solely based on their gender and not on their individual merits (statistical discrimination). An alternative and slightly less naive method is to award each female worker what her predicted salary would be according to the estimated salary equation for males. This approach has two problems. First, it creates an asymmetry between men and women in that each woman is paid exactly according to the male formula but men are paid according to the male formula only on average. So we could have a man and a woman with identical wage determining characteristics receiving different wages. The second problem is that there is no guarantee against the possibility that some women might actually receive a salary reduction. Another alternative would be to determine each female's salary as the sum of her predicted salary from the male wage formula and her own residual from the estimated female salary equation. Assuming that the wage models have been estimated by *OLS*, the female residuals will average to zero, thus guaranteeing that the original amount of salary discrimination has been paid out. This means that both men and women will be compensated on average according to the male wage formula. While it is still possible for a male and a female with the same observable wage determination characteristics to receive different wages, this will be because their individual residuals from their own estimated wage equations are different. The residuals can be viewed as the effects of unobserved productivity.

There still remains the potential problem that the adjusted salary for some women could be lower than their current salary. If this last algorithm were modified to give salary adjustments only to women who were predicted to receive positive salary increases, one can show that the average salary adjustment exceeds the original estimate of discrimination. Thus extra costs are imposed on the employer. Oaxaca and Ransom (2003) examines a modification of this algorithm in which women who would be awarded positive salary adjustments receive a specially calculated share of the original estimate of total salary discrimination. The shares are determined according to each of these individual's share of the total positive amount originally calculated for these women. All others receive zero salary adjustments. Since the total shares sum to 1, the total amount of underpayment will be fully allocated. One consequence is that some women might receive a smaller salary adjustment than originally calculated because they are in effect subsidizing women who would have received a negative adjustment. A variation of this algorithm takes into account a requirement that every female worker receive a minimal adjustment regardless of individual circumstances. Such a requirement could arise as a result of court imposed settlement. In this case satisfaction of the requirement that the exact amount of total underpayment be disbursed can result in the situation in which some women will receive salary adjustments less than that originally calculated. Again this is because the adjustment process provides a subsidy to those women who would have received zero or negative adjustments.

Complicating factors arise when working with the log wage (salary) specification and using the resulting estimates of discrimination to guide equity salary adjustments. The adoption of the log wage specification can be defended on the empirical grounds that the distribution of wages is fairly well approximated by a log normal distribution. On theoretical grounds Mincer (1974) argues that an individual's wage can be modeled as the product of the returns to prior investments in human capital over the life cycle. On the assumption that the error term in a log wage equation follows a normal distribution, it turns out that a worker's expected wage (W_i) conditioned on the wage determining variables is determined according to

$$W_i = \exp(X_i' \beta_i + 0.5\sigma_\varepsilon^2) \tag{13}$$

where σ_ε^2 is the variance of the error term in the log wage equation. Along the lines of JMP, we can think of the random error term as being generated according to the process $\varepsilon_i = av_i$, where v_i is a zero-mean random variable that reflects some index of unobserved productivity, a is a parameter that may be interpreted as the return to unobserved productivity. The variance of ε_i may be expressed as $\sigma_\varepsilon^2 = a^2\sigma_v^2$. Oaxaca and Ransom (2003) use a method of moments estimator to estimate σ_ε^2 for males and females separately. Equation (13) can be used to predict female wages using the estimated parameter vector $\hat{\beta}_m$ from the (log) wage equation for males. The question is should one use the estimate of σ_ε^2 obtained from the male sample or the estimate obtained from the female sample? If one believed that the variance σ_v^2 were identical for men and women but that the return to unobserved characteristics a were different between the sexes, then one would use the estimate of σ_ε^2 obtained from the male sample when predicting what women would earn on average if they faced the male wage determination process. As an alternative suppose that one believes that the return on unobserved characteristics (a) is the same for men and women but that there are gender differences in the variance (σ_v^2). In this case one would use the estimate of σ_ε^2 obtained from the female sample when predicting the wage for females using the male equation. This is the approach adopted in Oaxaca and Ransom (2003) but it is an arbitrary assumption as there is no way to know if a or σ_v^2 is the same for men and women. If one believes that both a and σ_v^2 are different for men and women, then there is no clear cut answer to the question of what estimated value of σ_ε^2 to use.

3. Parting thoughts

Hopefully, this paper has demonstrated that even under the most favorable circumstances, measuring labor market discrimination is not a straightforward proposition. Even if there were complete agreement on which variables should be taken into account and what the proper mathematical functional form should be for the empirical wage equation, there remains a host of judgments that need to be made before one can arrive at an estimate of discrimination and a process for correcting discriminatory processes and outcomes. Although it seems natural to interpret estimates of discrimination obtained as a residual gap in terms of the Becker model, there is no necessary reason to adopt this interpretation. The discrimination measure could just as well reflect the effects of statistical discrimination or monopsony power or some combination of these sources as well as of tastes and preferences.

In the spirit of unearthing more complicating factors, consider the assumption that in the absence of discrimination males and females should face the same coefficients in their wage equations. In other words should we expect that in a nondiscriminating labor market, males and females would be compensated according to the same wage determination formula? What if there were quality differences in the human capital acquired by men and women such as in on-the-job training (OJT) or in formal education? One would not expect the returns to these characteristics to be the same in a nondiscriminating labor market. One might argue that our models are indeed misspecified for both men and women because we should be controlling for the quality of the human capital variables. A counter argument could be that gender differences in the quality of human capital acquired may result from labor market discrimination or societal discrimination in general. Unfortunately, there is no simple way to determine the extent to which this is true. We as social scientists are not even able to measure quality in any convincing fashion.

Another argument for why one might not expect the coefficients in the wage equations to be the same for men and women in the absence of discrimination derives from the Mincer post-schooling investment model (Mincer, 1974). In a simple version of the Mincer model, experience and the square of experience are important determinants of log wages in a cross-section of workers. The concavity of the wage/experience profile is captured by a positive coefficient on experience and a negative coefficient on the square of experience. This functional form arises from the assumption that investment in OJT declines linearly through out one's working life. Abstracting from the effects of depreciation, the coefficient on experience depends on the rate of return to OJT and the fraction of time initially invested in OJT during the first year of work experience. The coefficient on the square of experience depends on these factors as well as on the length of the work life. If there were gender differences in the fraction of time initially invested in OJT and in the length of the work life, then there would be gender differences in the wage equation coefficients even if the rate of return to OJT were identical for men and women. Even if one could identify these parameters, not a trivial undertaking, how could one infer the extent to which gender differences in investment profiles are voluntary and how much is the result of discrimination? Of course if any of the difference is voluntary, then we could not expect the coefficients to be identical in a nondiscriminating environment.

In most empirical settings, the interest in conducting gender decomposition exercises focuses on observed gender differences in some variable of interest, e.g. wages, employment probabilities, prison sentences. Unless the model specification is linear in the parameters and *OLS* is used, there is no guarantee that the predicted sample means for each group will match the observed sample means. This is true of maximum likelihood estimation of probit models, tobit models, Heckman's selection model, etc. Non linearity raises issues about how to conduct decompositions in the context of non linearities, see Radchenko and Yun (2003), Yun (2004) and Yun (2005). One could proceed to decompose the predicted means, see Bauer and Sinning (2005). However, one can conduct an exact decomposition of the sample means by scaling the results by the discrepancy between the actual and predicted means. Gender differences in the prediction errors then become part of the decomposition, Sarnikar et al. (2006).

A final question is should we be using hourly wages or annual earnings to measure labor market discrimination against women? If men and women faced identical hourly wages but women worked fewer hours than men over a year's time, there would be a gender gap in annual earnings favoring men. The problem is that we do not really know with any degree of certainty how much of the gender gap in hours worked stems from voluntary labor supply and how much is conditioned by discriminatory constraints faced by women.

Even with all of the "scientific" apparatus we use to estimate unexplained gender wage gaps, what society ultimately labels as discrimination is decided by a complex cultural and political process. The best that we can hope for as social scientists is that our inquiry illuminates rather than obfuscates the debate over women's rights.

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