

## A primer on wage gap decompositions in the analysis of labor market discrimination

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**A PRIMER ON WAGE GAP DECOMPOSITIONS  
IN THE ANALYSIS OF LABOR MARKET DISCRIMINATION**

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Abstract

The traditional wage gap decomposition accounts for differences across demographic groups in wages and in the determinants of wages. The analysis decomposes the wage gap in a particular year into a portion explained by average group differences in productivity characteristics and a residual portion that is commonly attributed to discrimination. The low-cost data requirements and the intuitive appeal help to explain the popularity of the traditional procedure as a starting point for estimating the extent of wage discrimination. Researchers have subsequently introduced a number of extensions that build more detailed steps into the decomposition in order to provide a richer set of results. Evidence from these decompositions can provide a more finely-tuned benchmark as to the degree to which discrimination serves as an explanation for the presence and persistence of group differences in average wages.

## I. INTRODUCTION

Empirical studies of labor market discrimination have a long tradition in terms of the development of new methods, application to numerous groups and countries, and their testing of important labor market theories. Some studies have tested the neoclassical theory that industries with market power are characterized by greater discrimination in pay and employment. Other methods to examine the presence of discrimination include audit and correspondence studies, analysis of help-wanted advertisements, and the examination of lawsuits.<sup>1</sup> Straightforward regression analysis of the determinants of employment and wages, with control variables that include observed productivity characteristics as well as a binary variable for race or gender, also provides empirical estimates of discrimination. A negative and statistically significant coefficient on the race or gender variable, after controlling for characteristics such as education and experience, is interpreted as evidence of discrimination in the labor market.

Regression analysis underlies another widely-used method to estimate the extent of wage discrimination: the wage gap decomposition. The traditional decomposition, developed in Oaxaca (1973) and Blinder (1973), accounts for differences across demographic groups in wages and in the determinants of wages. The analysis decomposes the wage gap in a particular year into a portion explained by average group differences in productivity characteristics and a residual portion that is commonly attributed to discrimination. Like the single-equation regression approach, the traditional decomposition can be performed with just a single year of cross-section data and basic information on labor market characteristics. Both regression-based techniques are expected to yield similar conclusions about the extent of discriminatory treatment in the labor market. However, the decomposition procedure imposes less structure compared to a single regression model with a group dummy variable since the productivity characteristics are not constrained to have the same regression

coefficients across groups. The low-cost data requirements and the intuitive appeal help to explain the popularity of the traditional decomposition procedure as a starting point for estimating the extent of wage discrimination.

Researchers have subsequently introduced a number of extensions that build more detailed steps into the decomposition in order to provide a richer set of results. This chapter presents several alternative decompositions that extend the Oaxaca and Blinder type of approach with a unique dimension in order to further to assess wage gap determinants. Evidence from these decompositions can provide a more finely-tuned benchmark as to the degree to which discrimination serves as an explanation for the presence and persistence of group differences in average wages. For example, subsequent studies have utilized alternative wage structures as the reference for nondiscriminatory wages so that the decomposition is consistent with a more general model of discrimination. Newer work is also examining the residual component of wage distributions more closely with interpretations based on quantities and prices of unmeasured skills. More detailed explanations of wage gaps in particular years also include utilizing quantile regression techniques to understand the contribution of observed characteristics across the wage distribution and not just at the mean. Recent innovations also include adding a family dimension in order to explain the role of discrimination associated with female workers who have children.

In other work, adding a time dimension allows the researcher to examine changes over time in measured and unmeasured group-specific factors and in market returns to skills to the evolution of the wage gap. This trend technique provides a more detailed analysis of the wage gap compared to analyses that only perform the traditional decomposition with individual years of cross-section data. Results can show whether workers in a particular demographic group have gained over time relative to their counterparts in education and experience, whether the distribution of returns to skills

has narrowed or widened, and whether unmeasured group-specific factors have become more or less important over time. Closely related, adding a country dimension allows the researcher to examine differences across countries in wage structures and how the overall wage structure contributes to wage disparities between demographic groups. Another variant utilizes an occupational dimension and examines the extent to which pay inequality within occupation groups and employment across occupations explain the wage gap. The remaining sections discuss these methods in turn, with the exposition using the case of gender differences to derive each framework. However, all techniques are more generally applicable.

## II. TRADITIONAL DECOMPOSITION

The Oaxaca (1973) and Blinder (1973) decomposition procedure has become a standard tool of the trade for estimating the extent of wage discrimination. The approach is quite intuitive and can be performed with one year of micro-data containing worker characteristics. Household survey data, labor-force surveys, and census data have all been used in what amounts to hundreds of previously published works. For a given year, one can decompose the gender wage gap in several ways. The most common approach utilizes log-wage function estimates for men and for women. One estimates the following log-wage equation for male and female workers ( $i = m, f$ )

$$w_i = X_i\beta_i + v_i, \quad (1)$$

where  $w_i$  is the natural logarithm of hourly wages,  $X_i$  denotes a matrix of observed productivity characteristics,  $\beta_i$  denotes the vector of regression coefficients, and  $v_i$  is a random error term assumed to be normally distributed with a variance of  $\sigma_i^2$ . Productivity characteristics are best measured with variables that do not reflect discrimination by the employer. These variables commonly include years of education, years of labor-market experience, years of job-specific tenure, marital status, and

geographical location. Numerous studies include occupation and industry variables. However, if men and women obtain jobs in different occupations and industries as a result of employment discrimination, including these variables in the X matrix could lead to misleading conclusions about the extent of wage discrimination. A safe rule of thumb is to avoid including variables that may be endogenous to discrimination.

One can then describe the gender gap as follows

$$w_m - w_f = (X_m \beta_m - X_f \beta_f) + (v_m - v_f) . \quad (2)$$

If one evaluates the regressions at the means of the log-wage distributions, the last term becomes zero. Adding and subtracting  $X_f \beta_m$  to obtain worker attributes in terms of "male prices" gives

$$w_m - w_f = (X_m - X_f) \beta_m + X_f (\beta_m - \beta_f) + (v_m - v_f) . \quad (3)$$

The left-hand side of equation (3) is the total log-wage differential. On the right-hand side, the first term is the explained gap (the portion of the gap attributed to gender differences in measured productivity characteristics) and the second term is the residual gap (the portion attributed to gender differences in market returns to those characteristics). The remaining term is generally ignored as the decomposition is usually done at the means; otherwise, the sum of the last two terms is considered the residual gap. The convention in the literature is to use the male coefficients, with the implication that male wages better reflect the market payoffs for productivity characteristics than do female wages.<sup>2</sup>

Symptomatic of the "index number problem," results vary depending on the choice of male or female prices for weighting the decomposition equation. Alternative procedures have based the

decomposition on other reference wage structures, such as female wages or some weighted combination of male and female wages.<sup>3</sup> For example, Neumark (1988) has developed a decomposition that is consistent with a general model of discrimination in which employers have varying preferences for different types of workers. The model incorporates the practice of favoritism, in which men are overpaid, and discrimination, in which women are underpaid. When evaluated at the means, the Neumark procedure can be expressed as

$$w_m - w_f = (X_m - X_f)\beta^* + X_m(\beta_m - \beta^*) + X_f(\beta^* - \beta_f) , \quad (4)$$

where  $\beta^*$  represents the nondiscriminatory reference wage structure. The first term on the right-hand side shows the portion of the gap explained by differences in observed characteristics. The second term shows the extent to which the male characteristics are overvalued and the final term shows the extent to which the female characteristics are undervalued compared to the nondiscriminatory returns. Together, the second and third terms on the right-hand side would be attributed to discriminatory practices by employers. Note that if the male wage structure were to prevail in the absence of discrimination, then  $\beta^* = \beta_m$  and equation (4) would be equivalent to the Oaxaca decomposition in equation (3).

The wage returns in  $\beta^*$  are unobserved, and there are various options for estimating  $\beta^*$ . Assuming that employers care only about the relative proportions of males and females they hire rather than the absolute numbers, then the nondiscriminatory wage structure can be estimated from a wage equation using the pooled sample of male and female workers. The nondiscriminatory wage structure,  $\beta^*$ , is a weighted average of the wage structures for men and women, as follows

$$\beta^* = \Phi\beta_m + (1 - \Phi)\beta_f . \quad (5)$$

Oaxaca and Ransom (1994) propose using the cross-product matrices of the sample characteristics as weights for the estimated parameters  $\beta_m$  and  $\beta_f$ . They show that Neumark's solution is the same as their own in the case when the weighting matrix,  $\Phi$ , is defined as follows

$$\Phi = (X'X)^{-1}(X_m'X_m) , \quad (6)$$

where  $X$  and  $X_m$  are the matrices of observed productivity characteristics for the pooled sample and for the male sample.

Another issue associated with the traditional decomposition also relates to the choice of reference groups. In particular, Blinder's (1973) method isolates the contribution of the constant term as the unexplained part of discrimination. However, Jones (1983) argues that this method is flawed whenever the regressors include sets of dummy variables, since the estimated coefficient for the constant term will vary with the choice of the reference groups in constructing the dummy variables. Oaxaca and Ransom (1999) extend this critique and argue that the traditional decomposition cannot isolate the separate contribution of sets of dummy variables to the unexplained portion of the wage gap. They argue that the estimated contributions of dummy variables to the unexplained gap will vary with the choice of the reference group in structuring the dummy variables. Given this feature of dummy variables, it is only possible to estimate the relative contribution of a dummy variable to the unexplained portion of the wage gap.

### III. EXTENSIONS OF THE TRADITIONAL DECOMPOSITION

A more recent approach utilizes only the coefficients and standard deviation from the male regression.<sup>4</sup> By standardizing the error term, one can rewrite equation (1) as

$$w_i = X_i\beta_i + \sigma_i\epsilon_i , \quad (7)$$

where  $\epsilon_i$  is the standardized residual (meaning it is distributed with a mean of zero and a variance of one), and  $\sigma_i$  is the residual standard deviation of wages (meaning it is the monetary value per unit difference in the standardized residual). One can then specify the gender gap as

$$w_m - w_f = (X_m - X_f)\beta_m + \sigma_m(\theta_m - \theta_f) , \quad (8)$$

where

$$\begin{aligned} \theta_m &= (w_m - X_m \beta_m) / \sigma_m = \epsilon_m , \\ \theta_f &= (w_f - X_f \beta_m) / \sigma_m . \end{aligned} \quad (9)$$

The standardized residual for males,  $\theta_m$ , is the same as before ( $\epsilon_m$ ). The standardized residual for females,  $\theta_f$ , is based on the male coefficients and standard deviation (that is, the male prices). One is effectively reweighting the female wage equation using the coefficients and standard deviation from the male wage regression. This reweighting is equivalent to predicting the average wage that women would receive, given their qualifications, if they were paid like men. The  $X_i$  matrix contains the same set of observed characteristics as those specified for equation (1). As noted in Blau and Kahn (1996), if one uses the actual distribution of male residuals in implementing the decomposition, then this procedure is not imposing normality on the distribution of residuals.

The left-hand side of equation (8) is the total wage differential between men and women. On the right-hand side, the first term is the explained gap. The second term is the residual gap, which is a function of just the residual prices and the error terms. When evaluated at the means, the residual gap depends on the amount of male residual wage inequality ( $\sigma_m$ ) and the mean female's position in the male residual wage distribution ( $\theta_f$ ). Although equations (3) and (8) differ in their interpretation of the residual, they produce the same measures for the total, explained, and residual

gaps.

Wage gap decompositions have often needed to correct for selectivity bias, particularly if the analysis centers on differentials by gender. A sample of workers is censored because of a self-selection rule that determines whether the person works. This censoring overstates female wages and understates the gender wage gap. To avoid potentially misleading results, researchers typically control for selectivity bias using a two-step Heckman correction procedure.<sup>5</sup> A probit equation is estimated for all individuals in the working-age population predicts inclusion in the sample of wage earners, in order to calculate the inverse Mills' ratio. Independent variables include most of the variables found in the wage equation. In addition, unique identifying variables are included to identify the sample-selection effects. Such variables would predict labor-force entry but not wages.

Next, this ratio is included as an explanatory variable in Ordinary Least Squares (OLS) wage regressions. Since the ratio is a decreasing function of the probability of inclusion in the sample, a negative coefficient implies that higher wages are associated with greater probability of participation (Dolton and Makepeace, 1987). A negative sign implies that individuals from the lower end of the wage distribution are more likely to select out of the sample than those from the upper tail. This result is common for women given their lower labor force participation rates than men. For men, a negative sign could imply that the effect of excluding some low-wage workers from the sample (such as unpaid family workers) outweighs the effect of excluding some high-wage men from the sample (such as the self-employed). The magnitude of the selection effect is usually larger for women, although the selection effect is expected to decline over time as labor force participation increases.

An extension of the traditional decomposition developed in Joshi, Paci, and Waldfogel (1999) addresses the selection issues and wage penalties associated with the role of working women

as mothers. Rather than decomposing a male-female gap, the method focuses on the wage gap between mothers and women with no children. The procedure corrects for selection that varies not only by motherhood and childlessness but also non-employment, part-time employment, and full employment. After generating selection terms specific to motherhood and employment status, four separate wage equations are estimated for mothers and childless women with full-time and part-time jobs. Next, for both types of employment (full-time and part-time), the family gap is decomposed in line with the traditional procedure into a portion explained by differences between mothers and childless women in observed characteristics, and a portion comprising differences between mothers and childless women in compensation rates to particular characteristics. The procedure determines whether there is a direct pay penalty for women who have children and how this penalty differs from the penalty to engaging in part-time work.

Thus far the discussion has focused on estimations performed at the mean of the conditional wage distribution. However, recent advances also include performing the traditional decomposition across the full distribution of wages using quantile regression techniques. First introduced in Koenker and Bassett (1978) and further discussed in Buchinsky (1994, 1998), the quantile regression model can be considered a location model and written as

$$w_i = X_i\beta_\theta + u_{\theta_i}, \quad \text{Quant}_\theta(w_i|X_i) = X_i\beta_\theta . \quad (10)$$

As before, the notation  $w_i$  denotes the natural logarithm of wages for the sample of individuals  $i = 1$  to  $n$ ,  $X_i$  is the matrix of characteristics. Now  $\beta_\theta$  denotes the vector of quantile regression coefficients and  $u_{\theta_i}$  denotes the random error term with an unspecified distribution. The expression  $\text{Quant}_\theta(w_i|X_i)$  denotes the  $\theta$ th conditional quantile of  $w_i$ , conditional on the matrix of characteristics  $X_i$ , with  $0 < \theta < 1$ . Equation (10) does assume that  $u_{\theta_i}$  satisfies the restriction that  $\text{Quant}_\theta(u_{\theta_i}|X_i) = 0$ .

For a given quantile  $\theta$ , the coefficients  $\beta_\theta$  can be estimated by solving the following minimization problem

$$\min_{\beta} n^{-1} \sum_{i=1}^n \rho_\theta(w_i - X_i \beta_\theta), \quad (11)$$

where  $\rho_\theta(\lambda)$  is a check function defined as  $\rho_\theta(\lambda) = \theta\lambda$  for  $\lambda \geq 0$ , and  $\rho_\theta(\lambda) = (\theta-1)\lambda$  for  $\lambda < 0$ . One can trace the entire conditional distribution of log wages, conditional on the observed characteristics, by steadily increasing  $\theta$  from 0 to 1. Of course given the constraint placed by a limited number of observations, it is practical to estimate a finite number of quantile regressions. Each coefficient in the vector  $\beta_\theta$  is then interpreted as the marginal change in the  $\theta$ th conditional quantile of wages due to a marginal change in the regressor of interest. These coefficients can then be incorporated into the traditional wage gap decomposition as expressed in equation (3). Note that because equation (3) is no longer being evaluated at the means, the third term can no longer be ignored. Hence the wage gap at each quantile  $\theta$  in the distribution can be separated into a portion due to differences in observed characteristics, a portion due to differences in the returns to those characteristics, and a portion due to differences in residual wages.

#### IV. WAGE STRUCTURES OVER TIME

Results from traditional decompositions frequently indicate that a large share of the aggregate wage gap is not explained by observed productivity differences. Although changes in the residual gap are commonly attributed to changing patterns in wage discrimination, they may encompass changes in the overall wage structure that have little to do with discrimination. A trend decomposition technique, developed by Juhn, Murphy, and Pierce (1991), henceforth JMP, provides

a richer description of the sources of changes in the wage gap than the traditional decomposition. In adding a time dimension, the technique allows us to better understand the composition of the residual wage gap and hence the behavior of the total wage gap.

The trend decomposition continues from equation (8). Letting  $\Delta$  denote the male-female difference within a year in the variable that follows, and adding a subscript  $t$  for observations in year  $t$ , one can rewrite equation (8) as

$$\Delta w_t = \Delta X_t \beta_{mt} + \sigma_{mt} \Delta \theta_t . \quad (12)$$

Next, the rate of change in the gender wage gap between any two periods,  $t$  and  $s$ , can be described as

$$\Delta w_t - \Delta w_s = (\Delta X_t \beta_{mt} - \Delta X_s \beta_{ms}) + (\sigma_{mt} \Delta \theta_t - \sigma_{ms} \Delta \theta_s) . \quad (13)$$

In the next step, one chooses year  $s$  and male prices as the reference wage structure by adding and subtracting the term  $(\Delta X_t \beta_{ms} + \sigma_{ms} \Delta \theta_s)$  from the right-hand side. This manipulation yields the following trend decomposition equation

$$\begin{aligned} \Delta w_t - \Delta w_s = & (\Delta X_t - \Delta X_s) \beta_{ms} + \Delta X_t (\beta_{mt} - \beta_{ms}) \\ & + \sigma_{ms} (\Delta \theta_t - \Delta \theta_s) + (\sigma_{mt} - \sigma_{ms}) \Delta \theta_t . \end{aligned} \quad (14)$$

The first term on the right-hand side of equation (14) may be thought of as "measured quantities." This term represents changes over time in observed gender-specific characteristics, holding market returns fixed. For example, the gender wage gap may narrow over time due to an increase in women's educational attainment relative to that of men. The second term, considered "measured prices," represents changes in market returns, holding observed characteristics fixed. For

example, a decrease over time in returns to experience will cause the overall wage gap to narrow if men on average have higher observed levels of experience.

The third term is labeled "residual quantities." This term represents changes in unobserved gender-specific characteristics, which result in changes in the percentile ranking of women in the male residual wage distribution. Such unmeasured characteristics can include gender differences in labor force attachment due to intermittency, differences in unobserved skills, and wage discrimination by gender. As an example, reduced gender discrepancies in these characteristics could cause the ranking of the average female residual wage to rise from the 35<sup>th</sup> percentile to the 40<sup>th</sup> percentile of the male residual wage distribution, all else equal. The final term, considered "residual prices," reflects changes in male residual wage inequality. One can think of this last term as changes in the wage penalty for having a position below the mean in the male residual wage distribution. The gender-specific terms (first and third) reflect changes in the percentile ranking of women in the male overall wage distribution, while the wage-structure terms (second and fourth) reflect changes in the shape of the male overall wage distribution. In the computations, changes in the four components (measured quantities, measured prices, residual quantities, and residual prices) must sum to the total change for the period. Because some components work in opposite directions, it is possible for the change in one component to offset and even outweigh the contribution of changes in other components.

The JMP procedure, albeit quite useful, is not without its issues. First, the analysis suffers from the familiar index number problem in the choice of a reference group for the competitive wage returns. Also, results vary depending on the choice of base years. One can derive similar equations using different base years. Alternatively, to avoid possible extremes from any particular year, one can use the average across all years as the base. In using the average across all years, the year  $s$  terms

would represent mean quantity differentials across the sample years.

Another issue is the treatment of residual wages. Suen (1997) argues that separating the male and female residuals into a standardized residual ( $\theta$ ) and the standard deviation ( $\sigma$ ) can lead to misleading results because these terms are not independent from each other. In particular, increasing inequality in male residual wages causes the male residual wage dispersion to have thicker tails. This change alone in the shape of the male wage distribution will cause women to have a higher mean percentile ranking in the male distribution without any other changes having taken place. Figure 1 illustrates Suen's argument by showing how rising inequality in the distribution of male residual wages affects the gender wage gap.<sup>6</sup> The figure shows a widening in the dispersion of male residual wages from  $\sigma_{m1}f(\theta_m)$  in period 1 to  $\sigma_{m2}f(\theta_m)$  in period 2. One can see that the rising male residual wage inequality causes an increase in the mean female's position in the male residual wage distribution, from  $\theta_{f1}$  in period 1 to  $\theta_{f2}$  in period 2. Together, the growing dispersion in male residual wages with an apparent improvement in women's percentile ranking would lead to an observed stability in the residual wage gap between men and women, with  $gap_1 = gap_2$ .

Intuitively, more women have wages that rank toward the lower end of the male distribution. So when male residual wage inequality increases, the average female receives a lower wage for a given position in the male distribution. However, at the same time the average female's position in the male distribution is rising simply because the male distribution now has thicker tails. The JMP procedure would predict a growing wage gap as a result of more inequality in the returns to unmeasured skills. Any observed stability in the overall gender gap would have to be explained by a narrowing gender gap in unobserved gender-specific factors (residual quantities). Accounting for the increase in women's mean percentile ranking that resulted from the changing shape in the male distribution would also explain the overall stability in the gender gap. Suen's arguments imply that

researchers using the JMP procedure exercise caution in interpreting changes in residual wage gaps as changes in unobserved skills and returns to those skills. The use of panel data, more direct tests on the various impacts of changing wage inequality, or new methods based on quantile regression can each help to clarify the interpretation of wage residuals as unmeasured skills and their returns.<sup>7</sup>

## V. WAGE STRUCTURES ACROSS COUNTRIES

Researchers can also take advantage of cross-country data on wage determinants to add a country dimension to the traditional decomposition. The procedure is analogous to the JMP method, except that the time differences are replaced with country differences. Blau and Kahn (1996) developed this application in order to assess the importance of a country's overall wage structure relative to other countries in explaining international differences in pay gaps. The new procedure allowed them to address the puzzle of why the gender pay gap in the United States was so high compared to other countries, in the face of relatively favorable job market qualifications for U.S. women and a strong U.S. commitment to anti-discrimination legislation. More broadly, the decomposition along a country dimension allows one to examine the extent to which a country places a wage penalty on individuals with below-average productivity characteristics, compared to other countries.

The procedure continues from the traditional decomposition specified in equation (8). Again specifying  $\Delta$  as the male-female difference in the variable that follows, and adding a subscript  $c$  for observations in country  $c$ , one can rewrite equation (8) as

$$\Delta w_c = \Delta X_c \beta_{mc} + \sigma_{mc} \Delta \theta_c . \quad (15)$$

Equation (15) says that a country's wage gap can be divided into gender differences in observed characteristics,  $\Delta X_c$ , and gender differences in the standardized residual  $\theta$  (multiplied by the male

residual standard deviation in wages). Using equation (15), the difference in the gender wage gap between two countries,  $c$  and  $b$ , becomes

$$\Delta w_c - \Delta w_b = (\Delta X_c \beta_{mc} - \Delta X_b \beta_{mb}) + (\sigma_{mc} \Delta \theta_c - \sigma_{mb} \Delta \theta_b) . \quad (16)$$

One can choose country  $b$  as the reference point for wage structures by adding and subtracting the term  $(\Delta X_c \beta_{mb} + \sigma_{mb} \Delta \theta_c)$  from the right-hand side. This manipulation produces the following cross-country wage gap decomposition

$$\begin{aligned} \Delta w_c - \Delta w_b = & (\Delta X_c - \Delta X_b) \beta_{mb} + \Delta X_c (\beta_{mc} - \beta_{mb}) \\ & + \sigma_{mb} (\Delta \theta_c - \Delta \theta_b) + (\sigma_{mc} - \sigma_{mb}) \Delta \theta_c . \end{aligned} \quad (17)$$

The first term, “measured quantities,” represents the part of the pay gap that is explained by cross-country differences in the gender gap in observed productivity characteristics. For example, the pay gap in country  $c$  may exceed that of country  $b$  because women in country  $c$  the gender gap in experience may be relatively larger. The second term, “measured prices,” reflects cross-country differences in returns to labor market characteristics. For example, given a male advantage in years of experience, higher returns to experience in one country will yield a larger overall pay gap. The third term, “residual quantities,” reflects cross-country differences in the position of women in men’s residual wage distribution due to international differences in unmeasured gender-specific factors. This term captures the cross-country difference in the gender pay gap that would result if both countries had the same distribution of male residual wages and differed only from each other in the way that women ranked in the male distribution. The fourth term, “residual prices,” measures inter-country differences in residual male wage inequality. It captures the cross-country difference in the gender pay gap that would result if both countries had the same female rankings in the male residual

wage distribution, but they differed in the distribution of male residual wage inequality. This final term can be thought of as international differences in the wage penalty for having a position below the mean in the male residual wage distribution.

The first and third terms are gender specific and together reflect international differences in the percentile ranking of female workers in the male wage distribution. The second and fourth terms are particular to countries' wage structures and together reflect country differences in the shape of the male wage distribution. However, Suen (1997) has argued that this kind of decomposition of the residuals from the male wage regression into quantities and prices of unmeasured skills can generate misleading results. In more recent work, Blau and Kahn (2003) acknowledge that applying the JMP technique to country differences in pay gaps requires important assumptions. In particular, this application assumes that women are influenced by the same wage-setting forces that affect a country's distribution of male wages. Hence both the measured prices for males as well as the decomposition results for the residual prices for males are assumed to affect men and women in the same way. Blau and Kahn's more recent work provides a more direct test of the proposition that wage-setting institutions have played a major role in determining the gender wage gap in the United States. Results support their earlier findings, and indirectly the JMP procedure, that the United States' relatively high level of wage inequality is the main explanation for the country's relatively high wage gap between men and women.

## VI. OCCUPATIONAL DECOMPOSITION

An alternative decomposition method highlights the role of occupational segregation in explaining the wage gap. The method, first devised in Brown, Moon, and Zoloth (1980), henceforth BMZ, decomposes a wage gap into a component due to differences in employment shares across occupations, and a component due to within-occupations pay gaps. Each component is further

divided into a “justifiable” and “unjustifiable” portion, based on regressions performed with individual years of cross-section data and a few occupation categories. Since its initial application to United States data, this useful technique has been used to analyze labor markets in a wide range of countries.

The procedure begins with a description of overall mean wages as the weighted average of mean wages within occupations. Let  $W_{mt}$  and  $W_{ft}$  represent overall mean wages for male and female workers at time  $t$ , and let  $w_{mjt}$  and  $w_{fjt}$  represent the corresponding mean wage within occupation  $j$ . The gender wage gap can then be written as

$$W_{mt} - W_{ft} = \sum_j (\alpha_{mjt} w_{mjt} - \alpha_{fjt} w_{fjt}), \quad (18)$$

where  $\alpha_{mjt}$  is the proportion of total men’s employment in occupation  $j$  and  $\alpha_{fjt}$  is the proportion of total women’s employment in occupation  $j$ .

Next, the term  $\sum_j \alpha_{fjt} w_{mjt}$  is added and subtracted from the right-hand side of equation (18). This term represents the female overall average wage that would be observed if women received the same average wage within each occupation as men. The manipulation produces the following expression for the occupational decomposition

$$W_{mt} - W_{ft} = \sum_j (\alpha_{mjt} - \alpha_{fjt}) w_{mjt} + \sum_j \alpha_{fjt} (w_{mjt} - w_{fjt}). \quad (19)$$

The first term (the “across-occupations gap”) shows the effect of gender differences in the employment distribution across occupations, given male wages in these occupations. This term represents the portion of the gender wage gap which is explained by women’s relative concentration in certain occupations. The second term (the “within-occupations gap”) shows the effect of gender differences in wages within each occupation, given the female occupational structure. The

decomposition in equation (19) is similar to the traditional decomposition in that it applies to wages, employment, and worker characteristics at a given point in time.

The next step in the BMZ procedure is to further decompose the “across-occupations” gap into a portion attributed to gender differences in qualifications for the occupations (“justifiable”), and a portion attributed to differences between men and women in the structure of occupational attainment (“unjustifiable”).<sup>8</sup> Similarly, the “within-occupations” gap is divided into a portion attributed to productivity differences between men and women (“justifiable”) and a portion attributed to gender differences in market returns to those characteristics (“unjustifiable”). This decomposition of the “within-occupations” gap is analogous to the original Oaxaca procedure, with the caveat that the female occupational distribution is being held constant. The transformation of equation (19) is performed by adding and subtracting the term  $\sum_j \hat{\alpha}_{jft} w_{mjt}$  from the right-hand side and by decomposing the within-occupations gap in the usual way. The final BMZ equation becomes

$$\begin{aligned} W_{mt} - W_{ft} = & \sum_j (\alpha_{mjt} - \hat{\alpha}_{jft}) w_{mjt} + \sum_j (\hat{\alpha}_{jft} - \alpha_{jft}) w_{mjt} \\ & + \sum_j \alpha_{jft} (x_{mjt} - x_{jft}) \beta_{mjt} + \sum_j \alpha_{jft} x_{jft} (\beta_{mjt} - \beta_{jft}). \end{aligned} \quad (20)$$

The notation  $\hat{\alpha}$  denotes the share of female workers who would be employed in occupation  $j$  if females had the same occupational distribution as men. Performing the decomposition in equation (20) requires two separate sets of regressions. The first entails constructing the predicted variable  $\hat{\alpha}$  since the values for  $\hat{\alpha}$  are not actually observed. To estimate  $\hat{\alpha}$ , one predicts occupational attainment for men using a multinomial logit model of occupational attainment in which the probability that an individual obtains an occupation  $j$  depends on a set of labor supply and demand variables. The estimated parameters from the male sample are then combined with the female characteristics in order to predict the female occupational distribution. The second set of regressions

required for equation (20) entail running within-occupation OLS wage regressions in order to estimate the male coefficients  $\beta_{mjt}$ .

A new decomposition technique developed in Zveglich and Rodgers (2004) extends the BMZ approach by adding a trend analysis that allows the across- and within-occupations gaps to each have a pay dimension and an employment dimension. In contrast, the BMZ across-occupations gap has just an employment dimension and the BMZ within-occupations gap has just a pay dimension. Unlike BMZ, the trend analysis does not formally model the factors affecting women's occupational attainment, so it can say little about the justifiable and unjustifiable distinction for the employment-dimension terms. However, in avoiding the high computational costs of making such a distinction, the new procedure can be performed at a much finer level of occupational disaggregation than encountered in the BMZ study and its subsequent applications. The more recent trend analysis can be applied to either the unadjusted wage gap or the residual wage gap. The regression-adjusted approach generates results that reflect changes in occupational wages and employment shares, rather than changes in worker productivity characteristics and their returns.

The procedure follows from the decomposition in equation (19) by adding a time dimension in order to explain how changes in the distribution of a large range of occupational wages and shares over time affect trends in the wage gap. This added dimension is gained through mathematical steps that are analogous to the JMP derivation.<sup>9</sup> By differencing equation (19) between any two periods,  $s$  and  $t$ , one can derive an expression for changes in the gender wage gap in terms of changes in the occupational structure and in pay across and within occupations. Again letting  $\Delta$  denote the gender difference in any variable that follows, the change in the gender wage gap can be expressed as

$$\Delta W_t - \Delta W_s = \sum_j \Delta \alpha_{jt} w_{mjt} - \sum_j \Delta \alpha_{js} w_{mjs} + \sum_j \alpha_{fjt} \Delta w_{jt} - \sum_j \alpha_{fjs} \Delta w_{js}. \quad (21)$$

The next step is to choose year  $s$  as the base year for prices by adding and subtracting the term  $(\sum_j \Delta \alpha_{jt} w_{mjs} + \sum_j \alpha_{jft} \Delta w_{js})$  from the right-hand side of equation (21). This term represents the gender wage gap that would prevail in year  $t$  under the base year's occupational wage structure. The manipulation yields the following occupational decomposition of the wage gap

$$\begin{aligned} \Delta W_t - \Delta W_s = & \sum_j (\Delta \alpha_{jt} - \Delta \alpha_{js}) w_{mjs} + \sum_j \Delta \alpha_{jt} (w_{mjt} - w_{mjs}) \\ & + \sum_j (\alpha_{jft} - \alpha_{jfs}) \Delta w_{js} + \sum_j \alpha_{jft} (\Delta w_{jt} - \Delta w_{js}). \end{aligned} \tag{22}$$

Changes in the gender wage gap arise from four sources. The first term shows the contribution of changes in the relative employment distribution between men and women, commonly referred to as occupational segregation (“across-occupations employment effect”). For example, this effect can lead to a widening overall gender wage gap if pay structures within occupations are equitable, but women are becoming more concentrated in lower-paying occupations. The second term shows the contribution of changes in the wage structure across occupations (“across-occupations pay effect”). The degree to which occupational segregation affects the gender wage gap depends on the relative returns to various occupations. If changes in market returns favor female occupations, the gender gap will improve. The third term gives the contribution of changes in the female employment share within each occupation (“within-occupations employment effect”). For example, the overall wage gap will grow if women are becoming more concentrated in occupations that have inequitable pay structures, even if these occupations (such as senior officials and managers) are generally higher-paying occupations. The last term shows the contribution of changes in relative pay between men and women within each occupation (“within-occupations pay effect”). The extent to which wage disparity within occupations affects the overall gap depends on women's occupational

distribution. If women are concentrated in occupations that are experiencing more equitable compensation, then the gender gap will improve.

## VII. CONCLUSION

This paper has offered an intuitive exposition on the progression of techniques to decompose the gender wage gap, where all techniques can be generalized to analysis of other demographic groups and types of workers. The Oaxaca and Blinder technique still constitutes a starting point in many wage gap analyses, with a host of further options available to today's researchers for a more detailed look at the determinants of wage gaps and the potential role of wage discrimination in explaining those gaps. As discussed in this chapter, these options include examining alternative reference wage structures, the importance of unmeasured skills and their returns, wage gap determinants along the full distribution of wages, the role of changing wage structures over time in explaining wage gaps, the role of international differences in wage structures in explaining cross-country differences in wage gaps, and the importance of occupational segregation and pay gaps within occupations in explaining the overall gap. Of course all these decomposition techniques represent just one area in the empirical literature on discrimination, with other innovative techniques explored further in subsequent chapters.

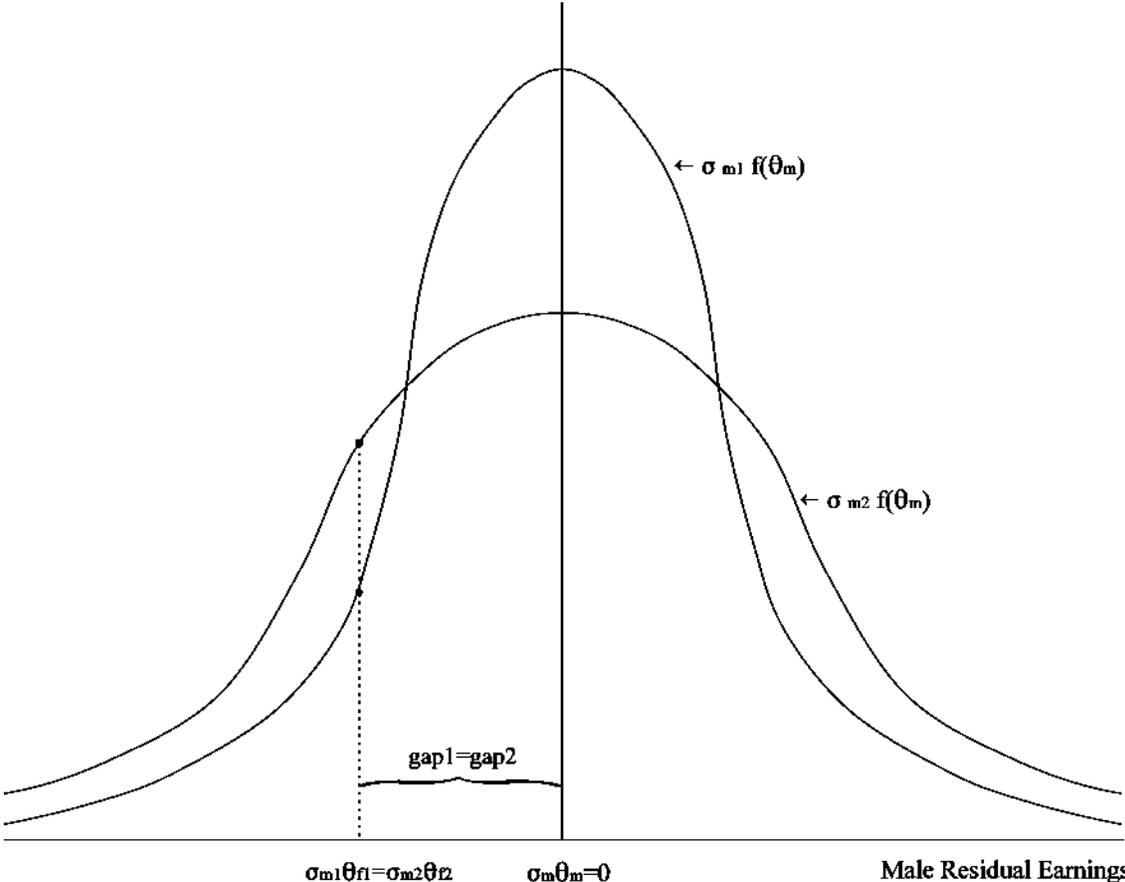
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**Figure 1.** Effect of Rising Male Residual Wage Inequality on Gender Wage Gap



## NOTES

1. For earlier reviews of these methods and results see Cain (1986), Darity and Mason (1998), and Altonji and Blank (1999).
2. See Goldin (1990) for a clear exposition on the use of male versus female coefficients.
3. Reimers (1983), Cotton (1988), Neumark (1988), and Oaxaca and Ranson (1994) have all addressed the index number problem using various reference wage structures.
4. This approach is used in Juhn, Murphy, and Pierce (1991) and in Blau and Kahn (1996). Also, Zveglic, Rodgers, and Rodgers (1997) compare this approach with the Oaxaca and Blinder approach.
5. Blau and Beller (1992) criticize the Heckman procedure for the high sensitivity of coefficient estimates to misspecification. Their alternative procedure, while correcting for changes in the self-selection rule, does not correct for the effect of self-selection in the base year or for any bias resulting from their own selection criteria. Newey, Powell, and Walker (1990) find that alternative semiparametric techniques to correct for sample selection yield results similar to the two-step procedure.
6. The discussion of the figure draws on Rodgers (1998).
7. For new methods that decompose changes over time in the wage gap using quantile regression techniques, see Machado and Mata (2003) and Albrecht, van Vuuren, and Vroman (2004).
8. A similar procedure, with further corrections for index number problems that occur in the choice of the reference wage structure, is found in Appleton, Hoddinott, and Krishnan (1999).
9. A related idea is found in Carrington, McCue, and Pierce (1996), which uses the time dimension to explain how changes in relative public-sector/private-sector wages and shares over time affect trends in the black-white wage gap.