Propensity score reweighting in gender pay gap analysis*

Philippe Van Kerm†
CEPS/INSTEAD, Luxembourg
and ISER, University of Essex, UK

Michela Bia‡
CEPS/INSTEAD, Luxembourg
and University of Florence, Italy

Abstract

This paper revisits estimation of Oaxaca – Blinder decomposition of wage differentials using weighted least squares in order to achieve greater robustness against model misspecification when the distribution of covariates are highly imbalanced across the groups compared. Monte Carlo simulations and an empirical application to gender wage differentials on the Socio – Economic Panel 'LIEWEN ZU LËTZEBUERG' (PSELL) show how WLS estimates are a much more accurate estimate of the wage differentials than OLS ones.

* This research is part of the MeDIM project (Advances in the Measurement of Discrimination, Inequality, and Mobility) supported by the Luxembourg 'Fonds National de la Recherce' (contract FNR/06/15/08) and by core funding for CEPS/INSTEAD from the Ministry of Culture, Higher Education and Research of Luxembourg.

† Philippe Van Kerm, CEPS/INSTEAD, Rue Emile Mark 44, B.P. 48, L-4501 Differdange, Luxembourg. Phone: +352 585855607 E-mail: philippe.vankerm@ceps.lu

‡ Michela Bia, CEPS/INSTEAD, Rue Emile Mark 44, B.P. 48, L-4501 Differdange, Luxembourg. Phone: +352 585855220 E-mail: michela.bia@ceps.lu

Introduction

Adjustment for group characteristic differences in standard estimation of wage differentials across population subgroups involves fitting wage regressions in each group and estimating predicted wages for a reference group based on coefficients from the other, comparison group. Validity of the adjusted wage differential estimates obtained after eliminating group differences in observable characteristics in this way therefore depends directly on the validity of the regression models estimated. Misspecification of the functional relationships between wage and covariates potentially bias wage differential estimates. Because of the use of 'out-of-sample' predictions from the comparison group to the reference group, misspecification is particularly problematic in the comparison group regression when the covariates are imbalanced between the two groups compared. In this situation, predictions in the reference group are predictions at points where there are relatively few data in the comparison group which therefore contribute little to the estimation of the regression coefficients. While this is unproblematic if the model is correctly specified for these data, the predictions are potentially biased if the model is misspecified.

The popular technique for studying wage differentials across population subgroups is the Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973)[§].It involves decomposing the difference in mean wage between two groups of interest (e.g., men and women, immigrants and natives, etc.) into an 'explained' component and an 'unexplained' (or `discrimination') component using wage regressions. The first factor picks up the effect of differences in observable group characteristics (with respect to, e.g., age, human capital) which can explain productivity and, therefore, wage differences. The second factor is the residual wage difference not explained by the group composition differences but attributed to how identical characteristics/productivity are 'rewarded' differently in the two groups.

In its simplest form, the procedure involves predicting for each agent in a reference group (say women) the counterfactual wage they would earn if their observable characteristics were rewarded as in a comparison group (say men). The counterfactual wage is constructed by running wage regressions in each group separately and making predictions for observations in the reference group using coefficient estimates from the comparison group[**].

Let μ^f and μ^m denote average log wage in, respectively, a sample of N^f female workers - the reference group - indexed $i = 1, \ldots, N^f$ and N^m male workers - the comparison group - indexed $j = 1, \ldots, N^m$. The raw, unadjusted, wage differential is

$$\Delta^U = \mu^m - \mu^f$$

and the Oaxaca-Blinder decomposition of this wage gap is

[§] This article is framed in terms of wage differentials, but the arguments apply to any continuous variable that can be modelled in a regression setting.

[**] Several variants of this basic model have been proposed; see Oaxaca and Ransom (1994). They typically involve modifying the reference group to construct a 'non-discriminatory' reference against which to make comparisons. We stick to the simplest and most common model of taking one group as reference and the other group as comparison group. The arguments and methods discussed here can be extended in a straightforward way to the alternative models. Extensions to comparisons of complete wage distributions, rather than comparisons of means, have also been developed.

$$\Delta^U = \underbrace{(\mu^m - \tilde{\mu}^f)}_{explained/productivity} + \underbrace{(\tilde{\mu}^f - \mu^f)}_{unexplained/discrimination}$$

where $\tilde{\mu}^f$ is the counterfactual average log wage of the reference group of female workers if their characteristics were rewarded as those of the comparison group of men. The second term, which we label Δ^A, is the wage differential adjusted for productivity differences. This is the key statistic of interest. It informs us about the magnitude of the average wage penalty suffered by our reference group of interest compared to the comparison group. In the evaluation studies terminology, this statistic is the impact of the 'treatment on the treated' (where "treatment" is belonging to the reference group rather than to the comparison group)[††].

Estimation of $\tilde{\mu}^f$ is done by first modelling the relationship between observed covariates X and log wage with a separate linear regression model in each of the two groups:

$$\log(w_i) = X_i\beta^m + e_i \qquad i = 1, \ldots, N^f$$

with e_i distributed $N(0, \sigma^f)$ for women and

$$\log(w_j) = X_j\beta^m + u_j \qquad j = 1, \ldots, N^m$$

with u_j distributed $N(0, \sigma^m)$ for men. Under these assumptions, μ^f, μ^m and $\tilde{\mu}^f$ can be expressed as

$$\mu^f = \frac{1}{N^f}\sum_{i=1}^{N^f} X_i\beta^f ,$$

$$\mu^m = \frac{1}{N^m}\sum_{j=1}^{N^m} X_j\beta^m ,$$

and

$$\tilde{\mu}^f = \frac{1}{N^f}\sum_{i=1}^{N^f} X_i\beta^m$$

The adjusted wage differential is then

$$\Delta^A = \tilde{\mu}^f - \mu^f = \frac{1}{N^f}\sum_{i=1}^{N^f} X_i(\beta^m - \beta^f) = \overline{X}^f(\beta^m - \beta^f)$$

where $\overline{X}^f$ is a row vector of covariate means in the reference (female) sample[4,5].

†† Evaluation techniques often attempt to estimate the 'average treatment effect'. By constrast, this statistic is largely irrelevant in the framework of this paper. Wage differential analysis typically consider "treatments" that can not be manipulated or assigned in any way by policies or else (one's gender, race, immigration status, etc.).This makes the average treatment effect of little interest. For example, we are interested in the average (estimated) wage penalty associated to being a women in the population of women, not the average penalty of being a women over the pooled population of men and women.

4,5 Note that, thanks to the additivity of the model in X, the contribution of an individual covariate to the aggregate wage differential is easily identified. The contribution of the kth component of X is the product of the kth element in $\overline{X}^f$ and kth element in $(\beta^m - \beta^f)$. The sum of the individual contributions is equal to the total adjusted wage differential.

One key feature of the Oaxaca-Blinder decomposition of wage differentials is that it is model-dependent, unlike alternative approaches recently advocated, notably by Ñopo (2008). The counterfactual wage for the reference group is an out-of-sample prediction from the regression model for the comparison group in the reference sample. The linear model assumption imposed on the relationship between log wages and covariates in each of the groups leads to the simple expressions just shown and provides easily interpretable estimates of the aggregate differentials and of the covariate contributions. All components are also easily computed. But (i) the approach is limited to comparisons of mean wages and does not identify higher order differences in the wage distributions of the groups compared, and (ii) correct inference relies on the validity of the modelling assumptions. Misspecification of the linear models may bias estimates of the adjusted wage differential estimates and the various components of the decomposition (including the impacts of individual covariates).

This paper is concerned with the second of these two limitations of the classic Oaxaca-Blinder decomposition. In particular, we will study the Shimodaira (2000) – Müller (2005) methods to context of wage differentials, we will analyze flexible estimation of the weights, that Shimodaira does not discuss in his study, using Monte Carlo simulations and we will apply these techniques to gender wage differentials on the Socio – Economic Panel 'LIEWEN ZU LËTZEBUERG' (PSELL).

[4,5] The explained part of the raw wage gap can be similarly expressed as

$$\Delta^U - \Delta^A = \mu^m - \tilde{\mu}^f = (\bar{X}^m - \bar{X}^f)\beta^m$$

where $\bar{X}^m$ is the row vector of covariate means in the comparison (male) sample.