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Abstract

The well-known Blinder–Oaxaca [Blinder, J. Hum. Resour. **8**(4), 436–455 (1973); Oaxaca, Int. Econ. Rev. **14**(3), 693–709 (1973)] decomposition divides the wage differential between men and women into a part, which can be explained by differences in individual characteristics, and another part, which is usually interpreted as discrimination. This decomposition neglects any distributional issues in evaluating discrimination, thus permitting undesirable compensation between positively and negatively discriminated women. Jenkins [J. Econ. **61**(1), 81–102 (1994)] has criticized this aspect, instead, preferring a distributional approach, where the entire distribution of experienced discrimination is evaluated. Following Jenkins [J. Econ. **61**(1), 81–102 (1994)], Del Río et~al. [J. Econ. Inequal. **9**(1), 57–86 (2011)] use a distributional approach, adapting the Foster–Greer–Thorbecke [Econometrica **52**(3), 761–766 (1984)] class of poverty indices to the study of discrimination.

Studies adopting this approach merit little attention as regards the issue of the separate measuring of wage discrimination and occupational discrimination. Alternatively, we have used the Foster–Greer–Thorbecke indices for measuring wage discrimination and occupational discrimination separately. Similar to the technique employed in the Brown–Moon–Zoloth decomposition [J. Hum. Resour. **15**(1), 3–28 (1980)], we have employed a multinomial model for estimating the theoretical distribution of women in occupations, which would result in the absence of occupational discrimination.

A Distributional Approach for Measuring Wage Discrimination and Occupational Discrimination Separately

R. Giaimo and G.L. Lo Magno

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The well-known Blinder–Oaxaca [Blinder, J. Hum. Resour. **8**(4), 436–455 (1973); Oaxaca, Int. Econ. Rev. **14**(3), 693–709 (1973)] decomposition divides the wage differential between men and women into a part, which can be explained by differences in individual characteristics, and another part, which is usually interpreted as discrimination. This decomposition neglects any distributional issues in evaluating discrimination, thus permitting undesirable compensation between positively and negatively discriminated women. Jenkins [J. Econ. **61**(1), 81–102 (1994)] has criticized this aspect, instead, preferring a distributional approach, where the entire distribution of experienced discrimination is evaluated. Following Jenkins [J. Econ. **61**(1), 81–102 (1994)], Del Río et al. [J. Econ. Inequal. **9**(1), 57–86 (2011)] use a distributional approach, adapting the Foster–Greer–Thorbecke [Econometrica **52**(3), 761–766 (1984)] class of poverty indices to the study of discrimination.

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1 Introduction

The standard approach to measuring wage discrimination is the Blinder–Oaxaca decomposition (B–O) (Blinder 1973; Oaxaca 1973), in which the hourly wage differential between men and women is decomposed as follows:

$$\ln \overline{W}_{\mathrm{M}} - \ln \overline{W}_{\mathrm{F}} = \left(\overline{Z}_{\mathrm{M}} - \overline{Z}_{\mathrm{F}}\right) \widehat{\beta}_{\mathrm{F}} + \overline{Z}_{\mathrm{M}} \left(\widehat{\beta}_{\mathrm{M}} - \widehat{\beta}_{\mathrm{F}}\right) \qquad (1)$$

where $\ln \overline{W}_{\mathrm{M}}$ and $\ln \overline{W}_{\mathrm{F}}$ are the means of the logarithms of observed hourly wage of men and women respectively, $\overline{Z}_{\mathrm{M}}$ and $\overline{Z}_{\mathrm{F}}$ are mean vectors (calculated for the observed sample) of individual characteristics, which are believed to affect wage, and $\widehat{\beta}_{\mathrm{M}}$ and $\widehat{\beta}_{\mathrm{F}}$ are OLS estimates, which are obtained by regressing, separately by sex, logarithm of hourly wage on those characteristics. The first part of the decomposition represents the wage differential explained by differences in individual characteristics, while the second is usually interpreted as discrimination. In the decomposition presented above, the differences in remuneration rates given by OLS estimates for regression coefficients are weighted by $\overline{Z}_{\mathrm{M}}$, while the differences in average endowments are weighted by $\widehat{\beta}_{\mathrm{F}}$. Other analogue decompositions, using different weightings, are provided by Reimers (1983), Cotton 1988, Neumark (1988) and Oaxaca and Ransom (1994).

Jenkins (1994) has criticized this standard approach because it does not adequately take into account the distribution of wage discrimination experienced by each woman. Indeed, it can be shown that the evaluating of wage discrimination, performed with the Blinder–Oaxaca decomposition, can lead to the conclusion of an absence of discrimination when positively discriminated women are compensated by negatively discriminated women, even when there is no conceptual doubt that discrimination is present. Moreover Jenkins (1994) has underlined a common aspect of poverty and discrimination: both can be viewed as a form of deprivation. Regarding poverty analysis, deprivation derives from a poverty line; in the case of discrimination, deprivation results from the wage which women would receive if no discrimination penalized them. In order to focus on distributional issues of discrimination, the distributional approach employs a two-step framework of poverty analysis: (1) defining a measure of individual discrimination for each woman; and (2) defining an index to summarize the entire distribution of the individual female discrimination. This discrimination index must satisfy some desiderable properties which are analogous to those defined in poverty analysis.

Del Río et al. (2011) agree with the distributional approach by Jenkins and they employ the family of indices by Foster, Greer and Thorbecke (1984) (FGT) (originally proposed for poverty analysis) for the study of wage discrimination:

$$D_{\alpha} = \frac{1}{n_{\mathrm{F}}} \sum_{i \in P} \left(\frac{\widehat{R}_{\mathrm{F}i} - \widehat{W}_{\mathrm{F}i}}{\widehat{R}_{\mathrm{F}i}} \right)^{\alpha}, \quad \alpha \geq 0 \qquad (2)$$

where n_{F} is the number of the women in the sample, $\widehat{R}_{\mathrm{F}i}$ is the expected wage which a woman would receive if she were not discriminated, $\widehat{W}_{\mathrm{F}i}$ is the unadjusted expected wage, P is the set of labels identifying discriminated women, i.e. women for whom $\widehat{R}_{\mathrm{F}i} - \widehat{W}_{\mathrm{F}i} > 0$. This index summarizes the distribution of individual discrimination, defined as $\widehat{R}_{\mathrm{F}i} - \widehat{W}_{\mathrm{F}i}$, in a single measure. The parameter α can be interpreted as an aversion parameter to discrimination: the larger is its value, the harsher is the penalty which the index attaches to a transfer of discrimination from a undiscriminated woman to a discriminated one. When $\alpha = 0$, the index is a head-count ratio of discriminated women, namely the share of discriminated women; when $\alpha > 0$ the index measures the intensity of discrimination.

The gender wage differential is determined by gender differences in productivity (which are related to human capital endowments), wage discrimination and occupational segregation. Wage discrimination occurs when two equally productive workers are paid a different amount for the same job. Occupational segregation occurs when women and men are differently distributed among occupations[1]; if women are more concentrated in low-paid occupations than men, this contributes to lowering the mean female wage. Occupational segregation can be due to occupational discrimination, that is the discriminatory behavior practised by employers, or be determined by personal preferences for a particular job.

In many analyses regarding the gender pay gap, the distribution of male and female among occupations is exogenously given, in the sense that it is not held to be generated by a discrimination process, thus masking an important source of discrimination. In this paper we will propose a methodology to separately evaluate the impact of wage discrimination and that of occupational discrimination, adopting the distributional approach by Del Río et al. (2011), which hinges on the FGT class of indices. In order to disentangle the two sources of discrimination, we need to evaluate the probability distribution of every female worker to be employed among occupations if she were treated as a man. A multinomial probit model will be separately estimated by sex to provide such information.

The remainder of this paper is organized as follows: Sect. 2 will review some basic concepts regarding segregation, occupational discrimination and their measurements; Sect. 3 will present our method; Sect. 4 will outline an empirical application on the Italian labour market data; the final section contains concluding remarks.

2 Segregation and Occupational Discrimination

Whilst female workers are confined to a limited set of occupations or sectors of economic activity, segregation represents a waste of human resources and an aspect of inefficiency in the labour market. It could, therefore, be said that the focus of

[1]For a review of the theories relating to occupational segregation by sex see Blau and Jusenius (1976) and Anker (1997).

labour research should be on equal opportunities rather then on market results only. Thus we think it is appropriate to disentangle the concept of segregation *tout-court* from that of occupational discrimination.

The difference in the distribution of men and women among occupations is measured by indices of segregation, which summarize how much the observed configuration departs from a proportional representation of the two sexes. The most common used segregation measure is the classic segregation index by Duncan and Duncan (1955) (D&D), also known as the *index of dissimilarity*, which is defined as:

$$D = (1/2)\sum\nolimits_{j=1}^{k} \left|(M_J/M) - \left(F_j/F\right)\right| \tag{3}$$

where M_J and F_j are the number of men and women respectively in occupation $j = 1, 2, \ldots, k$, and N_{M} and N_{F} are the number of male and female employees respectively. The D&D index is zero when the relative distributions of the two sexes are equal. When all men or women are concentrated into a single occupation, the index takes on the value of one. The index has a convenient interpretation: its value represents the share of women or men who are obliged to change occupation to eliminate segregation.

The D&D index and other segregation indices (Moir and Selby 1979; Karmel and MacLachlan 1998; Hutchens 2004) do not provide a measure of occupational discrimination, because they do not control for workers' personal characteristics. Indeed, segregation can be due to differences in human capital endowment, making it more likely for a particular gender to be employed in, for example, high status professions rather than unskilled jobs. Instead, occupational discrimination is a phenomenon which causes gender biases in hiring and promotion (Chzhen 2006) and it cannot be explained by strictly labour market factors.

A straightforward estimation strategy for occupational discrimination hinges on the theoretical distribution of women among occupations which would prevails if each woman in the sample had the same occupational attainment probability distribution, conditional on her characteristics, of a male worker. The impact of occupational discrimination on segregation can be measured via the comparison between the actual level of segregation and the case of free-from-discrimination occupational distribution.

Occupational attainment models employed in labour econometrics are models with qualitative dependent variable (Long 1997): the multinomial logit (or probit) model (Theil 1969), the conditional logit model (McFadden et al. 1968; McFadden 1974) and the ordered probit model (for a general discussion on the latter, see Greene 2003). We have used a multinomial logit model in the method proposed in this paper, according to which the estimated probability $\widehat{p}_{ij}$ to be employed in occupation j of a worker i of sex $\mathrm{S} = \mathrm{M}, \mathrm{F}$ and individual characteristics vector $\boldsymbol{X}_{\mathrm{S}i}$ is

$$\widehat{p}_{\mathrm{S}ij} = \frac{\exp\left(X_{\mathrm{S}i}\widehat{\gamma}_{\mathrm{S}j}\right)}{1+\sum_{h=2}^{k}\exp\left(X_{\mathrm{S}i}\widehat{\gamma}_{\mathrm{S}h}\right)}, \qquad \mathrm{S}=\mathrm{M},\mathrm{F} \tag{4}$$

where $\widehat{\boldsymbol{\gamma}}_{\mathrm{S}j}$ $(j = 1, 2, \ldots, k)$ are estimated parameters with $\widehat{\boldsymbol{\gamma}}_{\mathrm{S}0}$ arbitrarily set to $\mathbf{0}$.

The estimated share of women in occupation j, if the labour market treated them as they were men, is

$$\widehat{F}_j = \sum_{i=1}^{N_{\mathrm{F}}} \frac{\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{M}j}\right)}{1+\sum_{i=1}^{N_{\mathrm{F}}}\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{M}h}\right)} \tag{5}$$

which can be used to estimate the adjusted-for-discrimination D&D index:

$$D' = (1/2)\sum_{j=1}^{k}\left|(M_J/M) - \left(\widehat{F}_j/F\right)\right| \tag{6}$$

In empirical analysis, the D' index can be commented upon as a measure of segregation, which can be explained by differences in endowments (Brown et al. 1999) or compared with the unadjusted D index in evaluating the impact of occupational discrimination (Chzhen 2006; Miller 1987). Another estimation approach to estimating the impact of occupational discrimination, one which combines the D&D index with the multinomial logit model, is provided by Kal (2000).

The Brown–Moon–Zoloth (B–M–Z) decomposition (1980) is an appropriate procedure for evaluating the impact of occupational segregation (explained and unexplained by individual characteristics) on the gender wage differential. It basically decomposes the wage gap in four parts: the explained (*EW*) and the unexplained (*UW*) by individual characteristics of the within-occupation wage differential, and the explained (*EO*) and the not-explained (*UO*) by individual characteristics of the between-occupation wage differential. The *UW* component can be interpreted as wage discrimination, while the *UO* component as occupational discrimination. The B–M–Z decomposition is based on separate-by-sex estimates for the parameters of a multinomial logit models for occupational attainment ($\widehat{\boldsymbol{\gamma}}_{\mathrm{S}j}$, $\mathrm{S} = \mathrm{M}, \mathrm{F}$, $j = 1, 2, \ldots, k$) and on separate-by-sex-and-occupation estimates for the parameters of $k \times 2$ within-occupation wage regression models ($\widehat{\boldsymbol{\beta}}_{\mathrm{S}j}$, $\mathrm{S} = \mathrm{M}, \mathrm{F}$, $j = 1, 2, \ldots, k$). The decomposition is given by:

$$\begin{aligned}\overline{W}_{\mathrm{M}} - \overline{W}_{\mathrm{F}} &= \underbrace{\sum_{j=1}^{k} P_{\mathrm{F}j}\left(\overline{\boldsymbol{Z}}_{\mathrm{M}j} - \overline{\boldsymbol{Z}}_{\mathrm{F}j}\right)\widehat{\boldsymbol{\beta}}_{\mathrm{M}j}}_{EW} + \underbrace{\sum_{j=1}^{k} \overline{\boldsymbol{Z}}_{\mathrm{M}j} - \widehat{\boldsymbol{\beta}}_{\mathrm{M}j}\left(P_{\mathrm{M}j} - P'_{\mathrm{F}j}\right)}_{EO} \\ &+ \underbrace{\sum_{j=1}^{k} P_{\mathrm{F}j}\overline{\boldsymbol{Z}}_{\mathrm{F}j}\left(\widehat{\boldsymbol{\beta}}_{\mathrm{M}j} - \widehat{\boldsymbol{\beta}}_{\mathrm{F}j}\right)}_{UW} + \underbrace{\sum_{j=1}^{k} \overline{\boldsymbol{Z}}_{\mathrm{M}j}\widehat{\boldsymbol{\beta}}_{\mathrm{M}j}\left(P'_{\mathrm{F}j} - P_{\mathrm{F}j}\right)}_{UO}\end{aligned} \tag{7}$$

where $P_{\mathrm{M}j}$ and $P_{\mathrm{F}j}$ are the actual proportions of men and women respectively in occupation j, $P'_{\mathrm{F}j}$ is the estimated adjusted proportion of female workers in occupation j, calculated using (5), and $\overline{\boldsymbol{Z}}_{\mathrm{M}j}$ and $\overline{\boldsymbol{Z}}_{\mathrm{F}j}$ are the vectors of male and female mean individual characteristics respectively of workers in occupation j.

3 Measuring Wage Discrimination and Occupational Discrimination in the Distributional Approach

According to (Cain et al. 1986), the variables held constant in the statistical model, which is used to measure discrimination, should not be determined by the process of discrimination under examination. When occupational dummies are used in the B–O decomposition, gender differences in the distribution of workers among occupation are not justified by an occupational attainment model and the analysis thus ignores occupational discrimination. Furthermore the inclusion of occupational dummies in the wage equation is a questionable issue: while their exclusion allow for accounting for occupational discrimination, this estimation strategy, however, penalizes the accuracy of the model which explains wage (Miller 1987). Solberg (2005) claims that including dummy variables for occupation is not an adequate control and many authors found that the inclusion of occupational dummies in wage regressions reduces the unexplained component (Blau and Ferber 1987; Kidd and Shannon 1996). The B–M–Z decomposition addresses these methodological issues, but it does not take into account any distributional aspect of discrimination.

Our approach attempts to combine various features of the B–M–Z decomposition and the distributional approach by Del Río et al. (2011) in providing two separate measures for wage discrimination and occupational discrimination, which are distribution-sensitive.

Following (Brown et al. 1980), we first estimate two logit multinomial occupational attainment model with k occupations, separately by sex, using $\boldsymbol{X}_{\mathrm{M}i}$ and $\boldsymbol{X}_{\mathrm{F}i}$ individual characteristics vectors for men and women respectively. The two estimated multinomial model provide us with k estimated vectors of parameters $\widehat{\boldsymbol{\gamma}}_{\mathrm{M}j}$ for men and k estimated vectors $\widehat{\boldsymbol{\gamma}}_{\mathrm{F}j}$ for women. Thereafter, we use these estimates to assess the probability of a woman with characteristics $\boldsymbol{X}_{\mathrm{F}i}$ to be employed in occupation j if she were evaluated by the labor market as a man: $p'_{\mathrm{F}ij} = \frac{\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{M}j}\right)}{1+\sum_{h=2}^{k}\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{M}h}\right)}$, $\mathrm{S} = \mathrm{M}, \mathrm{F}$. We also estimate the following lognormal wage equations, separately by sex and occupation, using individual characteristics $\boldsymbol{Z}_{\mathrm{M}i}$ for men and $\boldsymbol{Z}_{\mathrm{F}i}$ for women:

$$\log W_{\mathrm{S}i} = Z_{\mathrm{S}i}\beta_{\mathrm{S}} + \varepsilon_{\mathrm{S}i}, \varepsilon_{\mathrm{S}i} \sim N\left(0; \widehat{\sigma}_{\mathrm{S}}^{2}\right), \quad \mathrm{S} = \mathrm{M}, \mathrm{F}$$

resulting in k OLS estimated vectors $\widehat{\boldsymbol{\beta}}_{\mathrm{M}j}$ and k analogous vectors $\widehat{\boldsymbol{\beta}}_{\mathrm{F}j}$. We estimate the female expected wage, which is adjusted for discrimination and conditioned to being employed in occupation j, as $\exp\left(Z_{\mathrm{F}i}\widehat{\beta}_{\mathrm{M}j} + \widehat{\sigma}_{\mathrm{M}}^2\right)$.[2] The estimated parameters are used to predict the expected wage in absence of occupational discrimination for each woman:

$$\widehat{U}_{\mathrm{F}i} = \sum_{j=1}^{k}\left[\frac{\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{M}j}\right)}{1+\sum_{h=2}^{k}\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{M}h}\right)}\exp\left(Z_{\mathrm{F}i}\widehat{\beta}_{\mathrm{F}j} + \frac{\widehat{\sigma}_{\mathrm{F}}^2}{2}\right)\right] \tag{8}$$

which is obtained by using the estimated male parameters in the occupational attainment model and the estimated female parameters in each within-occupation wage model.

By using the estimated female parameters in the occupational attainment model and the estimated male parameters in each within-occupation wage model, we obtain the expected wage for each woman in the absence of wage discrimination:

$$\widehat{R}_{\mathrm{F}i} = \sum_{j=1}^{k}\left[\frac{\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{F}j}\right)}{1+\sum_{h=2}^{k}\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{F}h}\right)}\exp\left(Z_{\mathrm{F}i}\widehat{\beta}_{\mathrm{M}j} + \frac{\widehat{\sigma}_{\mathrm{M}}^2}{2}\right)\right] \tag{9}$$

Finally, we calculate the unadjusted expected wage as

$$\widehat{W}_{\mathrm{F}i} = \sum_{j=1}^{k}\left[\frac{\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{F}j}\right)}{1+\sum_{h=2}^{k}\exp\left(X_{\mathrm{F}i}\widehat{\gamma}_{\mathrm{F}h}\right)}\exp\left(Z_{\mathrm{F}i}\widehat{\beta}_{\mathrm{F}j} + \frac{\widehat{\sigma}_{\mathrm{F}}^2}{2}\right)\right] \tag{10}$$

The distributional index of occupational discrimination we have proposed is obtained by using the FGT class of indices, where the role of "poverty line" is assumed by $\widehat{U}_{\mathrm{F}i}$:

$$\widehat{D}_{\mathrm{O}}^{\alpha} = \frac{1}{n_{\mathrm{F}}}\sum_{i\in P_{\mathrm{O}}}\left(\frac{\widehat{U}_{\mathrm{F}i} - \widehat{W}_{\mathrm{F}i}}{\widehat{U}_{\mathrm{F}i}}\right)^{\alpha}, \quad \alpha \geq 0 \tag{11}$$

where the set P_{O} identifies the women for whom $\widehat{U}_{\mathrm{F}i} - \widehat{W}_{\mathrm{F}i} > 0$ (that is, the women which can be considered *discriminated* in the occupational sense) and α can be interpreted as an aversion parameter to occupational discrimination.

[2] Remember that if $\log W_{Si} \sim N\left(\boldsymbol{Z}_{Si}\boldsymbol{\beta}_S; \widehat{\sigma}_S^2\right)$ then $W_{Si} \sim \log N\left(\boldsymbol{Z}_{Si}\boldsymbol{\beta}_S; \widehat{\sigma}_S^2\right)$, thus $E\left(W_{Si}\right) = \exp\left(\boldsymbol{Z}_{Si}\boldsymbol{\beta}_S + \widehat{\sigma}_S^2\right)$. The estimator $\exp\left(\boldsymbol{Z}_{Si}\widehat{\boldsymbol{\beta}}_S + \widehat{\sigma}_S^2\right)$ is biased but consistent for $E(W_{Si})$.

Table 1 Indices of occupational discrimination $\widehat{D}_{\mathrm{O}}^{\alpha}$ and wage discrimination $\widehat{D}_{\mathrm{W}}^{\alpha}$ for different values of aversion parameter α calculated for Italy and Italian regions

	$\widehat{D}_{\mathrm{O}}^{\alpha}$				$\widehat{D}_{\mathrm{W}}^{\alpha}$			
α	North	Center	South	Italy	North	Center	South	Italy
0	0.132	0.037	0.004	0.082	0.993	0.987	0.973	0.987
1	0.004	0.000	0.000	0.002	0.154	0.140	0.124	0.144
2	0.000	0.000	0.000	0.000	0.028	0.024	0.020	0.025
3	0.000	0.000	0.000	0.000	0.005	0.005	0.004	0.005

Source: Authors' calculations using the Italian Eu-Silc 2006 data

Our distributional index of wage discrimination is given by:

$$\widehat{D}_{\mathrm{W}}^{\alpha}=\frac{1}{n_{\mathrm{F}}}\sum\nolimits_{i\in P_{\mathrm{W}}}\left(\frac{\widehat{R}_{\mathrm{F}i}-\widehat{W}_{\mathrm{F}i}}{R_{\mathrm{F}i}}\right)^{\alpha},\quad \alpha\geq 0 \tag{12}$$

where the set P_{W} identifies the women for whom $\widehat{R}_{\mathrm{F}i}-\widehat{W}_{\mathrm{F}i}>0$ (that is, the women who can be considered purely-wage-discriminated) and α can be interpreted as an aversion parameter to wage discrimination.

4 Empirical Analysis

We employed our distributional indices to analyze gender discrimination in Italy, using the Eu-Silc Italian data for 2006. The sample under consideration comprised employees (minimum age 16-years old), who were in receipt of a paid work when interviewed. The sample included 8,333 men and 6,677 women. Eight of the nine occupations of the Isco-88 (COM) one-digit classification were considered in our analysis, excluding the armed forces (the exclusion is due to the low number of women in this category). Variables used for the multinomial logit models were: number of years in education, years of work experience and dummy variables for the region of residence (the north, center or south of Italy). Variables used for the lognormal wage equations varied from occupation to occupation, being selected according to tests of significant for regression coefficients; they were generally the same as those used in the multinomial models plus worked hours in a week and economic activity. In calculating our discrimination indices, we use different values of the parameter α to provide discrimination evaluations at different levels of aversion to discrimination (the interpretation is straightforward only when $\alpha=0,1$). The results are shown in Table 1 below.

These results demonstrate that 98.7 % of Italian women suffer wage discrimination, while women suffering occupational discrimination are only 8.2 %. A higher value for the parameter α, the more the index reflects aversion to discrimination. Discrimination is more marked in the north of Italy but differences between the various regions do not seem to be significant for higher values of α. The ranking of the evaluation of occupational and wage discrimination for Italian regions does not change for different values of α, thus providing a clear picture of the two discrimination forms. We further demonstrated that wage discrimination in Italy is more significant than occupational discrimination, thus providing us with an interesting interpretation of the gender pay gap.

5 Conclusions

The classic approach to measure discrimination, given by decomposition techniques at mean values of individual characteristics, can be considered as an approximate way to summarize individual discrimination. Indeed, it does not take into account various important properties which would characterize an effective discrimination index, such as, for example, the transfer principle. Instead, the distributional approach focuses its attention on the entire distribution of discrimination and satisfies desiderable properties which are analogous to those commonly used in poverty analysis.

Another issue in analyzing labour discrimination is the controlling for individual characteristics which determine the probability to be employed in an occupational category. The (Brown et al. 1980) decomposition gives a well-founded estimation strategy for this type of control, but relies on an evaluation at mean values of individual characteristics.

Our approach is based on an occupational attainment model, similar to that of (Brown et al. 1980), and on estimates for the expected wage, as adjusted for occupational discrimination and the expected wage, as adjusted for wage discrimination. We measured two forms of individual discrimination (of occupational and purely-wage type) and aggregate the corresponding distributions using the Foster et al. (1984) class of indices; the latter were originally used in poverty analysis and also employed in discrimination analysis by Del Río et al. (2011). Thus, we could provide two separate measures of wage discrimination and occupational discrimination.

The empirical analysis which we performed for the Italian labour market demonstrated that wage and occupational discrimination are quite different in their extent and intensity. This fact can yield important information regarding the functioning of the Italian labour market, guiding policy makers towards specific areas of intervention in gender issues.

We will conclude by outlining several theoretical challenges. Every discrimination analysis relies on the occupational detail chosen. We use the Isco-88 Com classification of occupations at a very aggregated detail, and we are aware that results could change in accordance with a different occupational detail. Furthermore, international standards classification of occupations can lead to a segregation evaluation which depends on the logic of the classification itself and, therefore, another classifications could be useful in future research.

A final consideration must be mentioned, regarding the meaning of segregation which cannot be explained by individual characteristics. As segregation can be due to employees' individual preferences (in addition to occupational discrimination being practiced by employers), it may not be clear from ordinary empirical analysis how much of the not-explained segregation can be due to discrimination. Little research currently exists regarding the estimation strategy in providing separate measures of the impact of the two phenomena and this could lead the way to future research.

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