The measurement of gender wage discrimination: the distributional approach revisited

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ABSTRACT

This paper presents the advantages of taking into account the distribution of the *individual* wage gap when analysing female wage discrimination. The limitations of previous approaches such as the classic Oaxaca-Blinder and the recent distributive proposals using quantile regressions or counterfactual functions are thoroughly discussed. The new methodology presented here relies on Jenkins' (1994) work and proposes the use of poverty and deprivation literature techniques that are directly applicable to the measurement of discrimination. As an illustrative example we measure female wage discrimination in Spain aggregating individual wage gaps estimated with OLS and quantile regressions.

Keywords: distributive analysis, gender, wage discrimination.

JEL Classification: J16, J31, J71.

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The lower wages paid to female workers in comparison with males in most labour markets can easily be checked empirically using individual data on wages. The fact that these wage differentials are not justified in terms of labour productivity is usually known as *gender wage discrimination*.

Inequality arguments led Jenkins (1994) to propose the adequacy of the procedures used to measure poverty for the analysis of wage discrimination. Indeed, both phenomena have strong similarities. More precisely, both imply some income or wage gap: either individual income does not provide a *minimum level of resources* (Atkinson, 1998), or, similarly, the female wage is below what she would receive *were she male but otherwise had identical attributes*. From this perspective, the female wage gap reveals itself as genuinely individual, implying that its distribution in the population under study should play a crucial role in its measurement.

Following the proposals developed by Sen (1976) in the poverty literature, Jenkins (1994) underlines that there are three basic questions to answer if we aim to analyse discrimination rigorously: how to 1) define direct wage discrimination; 2) identify which individuals suffer discrimination and in what quantity; and 3) sum up the wage gaps using an index that verifies a series of desirable normative properties. The classical methodology, widely used in empirical work, limits the analysis to the calculation of the *mean* wage gap. In doing so we are, implicitly, imposing the same weight on each wage gap independent of its relative relevance or value within the wage distribution. Jenkins (1994), instead, suggests that researchers use the individual wage gap and focuses the discussion on the analysis of the distribution of this gap using the theoretical advances in poverty and deprivation research. Thus, in this context, what is relevant is precisely the difference between what the individual would earn if she did not face discrimination and what she actually earns. The analysis then focuses on the indicators that summarise all these differences using weights for the different discriminatory experiences incorporating a wide range of different judgements about how these gaps are aggregated in a systematic yet transparent way.

Some recent lines of research that aim to include distributional aspects propose the use of quantile regressions in the estimation of wage equations in order to increase the number of points in the earnings distribution at which the wage gap is evaluated. Other proposals include a variety of techniques to estimate counterfactual earnings distribution functions in order to compare them with the original wage distribution and quantify the effects of wage differentials throughout the whole earnings range. Certainly both approaches allow us to obtain more information from the observed wage distributions. Nevertheless, in both cases, they avoid considering the individual aspect of discrimination.

Our paper examines in detail the advantages of using a new distributional methodology proposed by Jenkins (1994) in comparison with other available distributional approaches for the analysis of wage discrimination. We should be aware, however, that the estimation of wage equations using quantile regressions and the use of normative measures of discrimination *á la Jenkins* are complementary techniques. Therefore, as we will present in an empirical exercise, it is possible to use quantile regressions to identify the individual levels of discrimination and then use normative measures that allow us to sum up the different estimated wage gaps.[1]

The main contribution of this paper is that of proposing a new normative framework for the study of wage discrimination based on the poverty and deprivation literature. In order to do this we rely on Jenkins (1994) and Shorrocks (1998) work. We detail the general limitations of the most usual distributive techniques and propose a variety of discrimination measures that allow us to aggregate individual wage gaps. These measures are explicit about the value judgements they imply and on which we would aim to reach an agreement. This allows us to rank, in a robust way, a list of women's earnings' distributions in terms of their discrimination level and compare the discriminatory experiences of women with different attributes. In order to provide empirical evidence on the theoretical contribution of the paper, we contrast the advantages of our approach using a sample of Spanish data. This last exercise allows us to quantify the improvement afforded by the use of quantile regressions in respect to OLS classical regressions in the process of the individual wage gap identification. We should underline here also that, even if we recurrently refer to female wage

[1] This procedure is not applicable when using the counterfactual functions approach, given that this method does not provide us with individualised wage gaps.

discrimination, the theoretical contributions of this paper are readily applicable to any other source of discrimination (race, religion, sexual orientation, origin, etc.).

The paper is organised as follows. Section 1 presents the classic approach to the measurement of discrimination and gives a sound justification of the importance of considering distributive aspects in discrimination measurement. In Section 2 we discuss the limitations of a variety of distributional techniques recently used in the study of wage discrimination. Section 3 presents our proposal for the measurement of discrimination and details its main contribution. In Section 4 we provide empirical evidence on the advantages of our techniques on a sample of Spanish wage microdata. Finally, Section 5 concludes by presenting our main findings.

1. THE RELEVANCE OF THE DISTRIBUTIVE APPROACH IN ANALYSING WAGE DISCRIMINATION

1.1 Wage discrimination: The identification problem

These days there is wide consensus on identifying gender wage discrimination as the difference in earnings between male and female workers who are otherwise identical in their attributes and thus in their expected productivity. In order to detect its presence and to measure its relevance, researchers have traditionally estimated wage equations conditional on a list of variables which, *a priori,* are potential determinants of the individual salary.

Two separate *mincerian* log wage equations for males and females are estimated:

$$\ln(y_{hi}) = Z'_{hi}\beta_h + u_{hi}$$
$$\ln(y_{mi}) = Z'_{mi}\beta_m + u_{mi}$$

where h refers to males, m to females, and y_i stands for the i^{th} worker hourly wage, Z'_i is the vector of characteristics, β are the characteristics' rates of return, and u_i is the corresponding error term. Once the model is estimated we are able to predict both the estimated wage of a female worker, $\hat{y}_{mi}$, and her potential wage if her attributes were remunerated as if she were male, $\hat{r}_{mi}$:

$$\hat{y}_{mi} = \exp(Z'_{mi}\hat{\beta}_m)$$

$$\hat{r}_{mi} = \exp(Z'_{mi}\hat{\beta}_h)$$

The individual wage gap $(\hat{r}_{mi} - \hat{y}_{mi})$ reflects the estimated wage discrimination experienced by a female worker *i*, $(\hat{r}_m - \hat{y}_m)$ being the distribution of the estimated discrimination in the female workers group.[2]

1.2 Wage discrimination: The aggregation problem

Traditionally based on OLS estimations of wage equations, discrimination has been evaluated in the mean distribution of the characteristics, and has thus quantified the wage discrimination suffered by the *mean* female worker when compared to the *mean* male worker. This is precisely the approach proposed by Oaxaca (1973) and Blinder (1973) in their seminal articles, which has been recurrently utilised in the literature on wage discrimination. In the original Oaxaca-Blinder decomposition the mean observed wage gap is divided into two components: a first component, A, would quantify the labour market premium on the mean differences in characteristics between genders, while the second component, B, would show how differently the labour market rewards gender evaluated at the mean female characteristics:

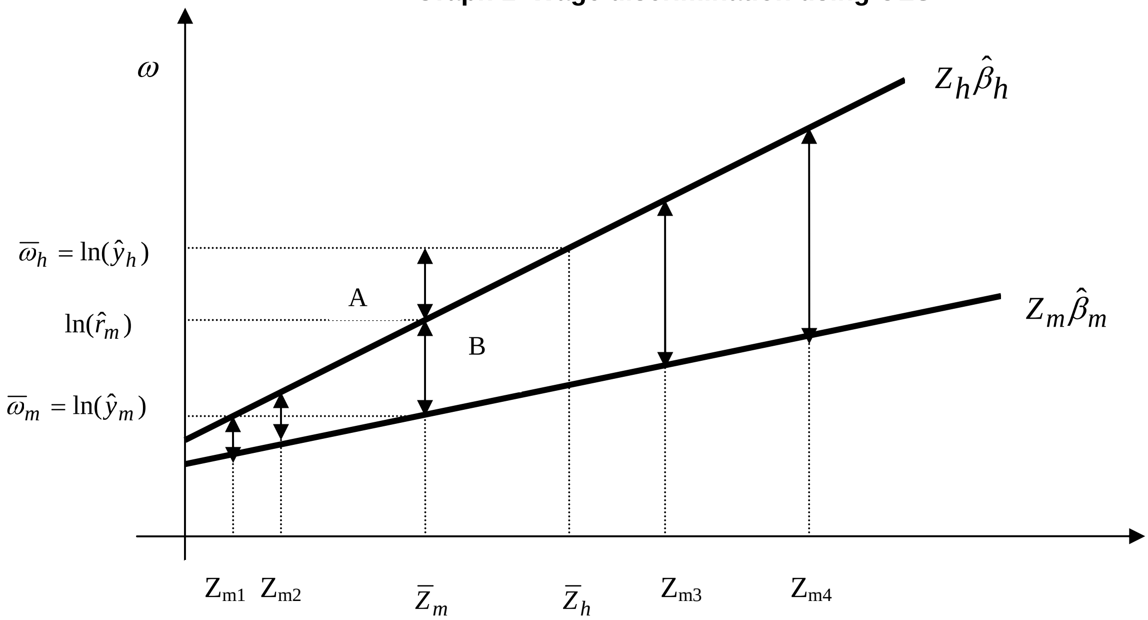
$$\overline{\ln(y_h)} - \overline{\ln(y_m)} = (\overline{Z'_h} - \overline{Z'_m})\hat{\beta}_h + \overline{Z'_m}(\hat{\beta}_h - \hat{\beta}_m) = \mathrm{A} + \mathrm{B}\ .$$

Graph 1 shows, in the unidimensional case, that the second component denotes the wage penalty the mean female worker faces given that she has a different remuneration of attributes compared to males. Even if seldom noted, it is easy to check that B is the mean of the differences of predicted male and female wages estimated for each woman in the population (in our example: Z_{m1}, ..., Z_{m4}). The choice of the male wage structure

[2] In his classic survey Cain (1986) offers a detailed reference to the most important theories that attempt to explain discrimination and discusses models based on Mincer (1974). Recently, in Kunze (2000) we find a revision of the most relevant empirical literature in trying to achieve a consistent estimation of the parameters in wage equations.

as the non-discriminatory reference is equivalent to considering discrimination as the disadvantage of any group with respect to the most favoured group. This would not be true in the case of choosing some other reference.

Graph 1. Wage discrimination using OLS



Whatever the non-discriminatory remuneration structure of reference, the use of the wage distribution mean is a large waste of information. In the first place the mean does not allow for differences in the discriminatory experience at different points of the wage distribution. Furthermore, and most importantly, it implies assuming that to give the same weight to each different individual discrimination experience is a desirable way of aggregating wage gaps, independently of the actual degree of discrimination suffered by each individual. This all implies implicitly, and in an obscure way, the imposition of value judgements that are rather implausible from a normative point of view. Moreover, there has been little, if any, discussion in the literature on the adequacy of these assumptions. This is all most probably due to the attractive mathematical properties of the mean and also to the general lack of discussion of normative implications in discrimination measurement. In this context, we consider that the study of discrimination should aim to rely on flexible and complete measurements that allow us to identify the differences in results throughout the wage range when we incorporate, explicitly, the different judgements in the aggregation of individual information.

A number of papers have introduced a variety of econometric techniques in order to incorporate distributive aspects in the comparative analysis of wage distribution. Within the studies that aim to measure gender wage discrimination, Blau and Khan (1996, 1997) explained the international differences in female wage deficiency and their evolution in time using the methodology proposed by Juhn, Murphy and Pierce (1991).[3] Fortin and Lemieux (1998) analysed the wage gap throughout various years using *rank regressions*. Most recently, Bonjour and Gerfin (2001) applied the methodology proposed by Donald, Green and Paarsch (2000) to decompose the wage gap in Switzerland. Finally, other papers have used quantile regressions in order to decompose the gender wage gap at different points of the wage distribution. Examples of this are Reilly (1999) and Newell and Reilly (2001) in the analysis of ex-communist countries in transition, Albrecht, Björklund and Vroman (2003) in their study of the "glass-ceiling" in Sweden,[4] and García, Hernández and López-Nicolás (2001), Gardeazábal and Ugidos (2004), and Dolado and Llorens (2004) in their works for the Spanish labour market.

We maintain that all these recent approaches to the analysis of discriminatory practices are a clear improvement on other previous ones but present, nevertheless, some important limitations.

2. THE LIMITATIONS OF RECENT DISTRIBUTIVE APPROACHES

2.1 The comparison of conditional wage distributions: distributive aspects and conceptual errors in measuring discrimination

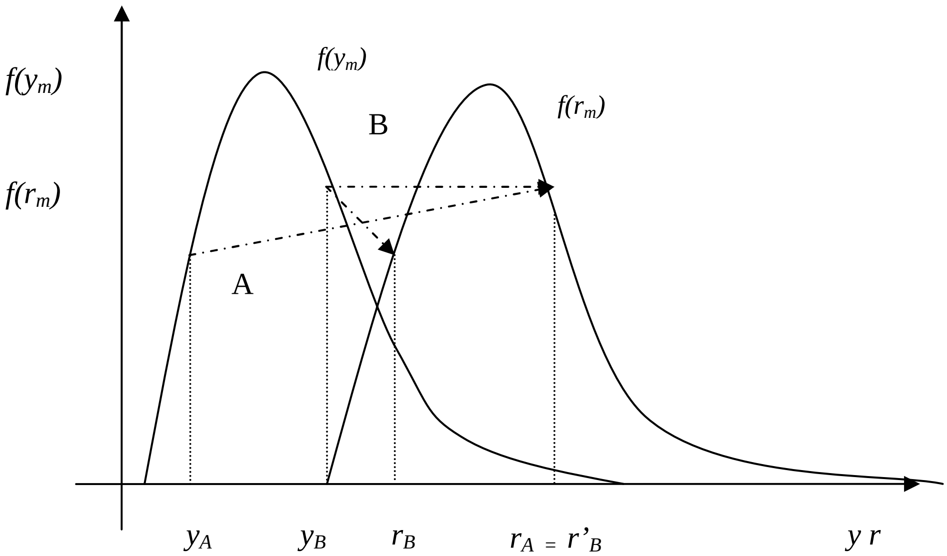
When moving from $\hat{y}_m$ to $\hat{r}_m$ wage distributions it will not come as a surprise that some female workers change their relative positions. Thus it may well be that part of the earnings differentials between both distributions, evaluated at each quantile, are the result of the different discriminatory experiences of female workers. Let us assume that we depart from such a wage distribution as the density function $f(y_m)$ on the left hand

[3] This methodology allowed them to take into account the role played by the wage structure in the explanation of the gender wage gap.
[4] These authors use techniques developed by Machado and Mata (2004) where quantile regressions are used in order to estimate counterfactual density functions.

side of Graph 2. Suppose that once we eliminate direct wage discrimination the new density function moves uniformly to the right $f(r_m)$. In this particular case, the distributive analysis using quantile differences would conclude that all female workers experience the same absolute level of discrimination, whatever their wage.

Nevertheless, this may not be necessarily true. It may be the case, as depicted in the graph, that all type A women, that initially earned y_A, earn r_A when the discriminatory component is eliminated. Additionally, a similar number of those female workers that were earning y_B could be experiencing a lower wage change once we eliminate discrimination and thus appear in r_B. The rest of type B women would reach the same wage level as females in A, the level r'_B. Obviously, the level of discrimination suffered by group A is much larger than that suffered by group B, but neither the study of the differences in the mean (as expected) nor the comparison of quantile counterfactual distributions would detect it.

Graph 2. Wage discrimination using counterfactual densities



In other words, when comparing density functions we are not only quantifying discrimination but also the re-orderings in the wage distribution. In this way, this measurement of discrimination is *contaminated* in the presence of mobility between quantiles.

The comparison of the mean, the variance or quantiles of the wage distribution functions does not allow us to consider the individual discriminatory experience. This strategy makes it impossible to assure that a certain decile suffers more or less discrimination than another, given that the women that initially were placed in each of them may not be the same women, once individual discrimination is taken into account. Nevertheless various techniques in the literature on gender wage discrimination are based implicitly on the assumption that these are the same women. Clearly, these papers should observe caution in the interpretation of some of their results.[5] The use of these techniques should remain within the interesting study of the distributive effects of discrimination but should never be confused with a way of identifying the actual level of discrimination in the wage distribution.[6]

2.2 The need for normative measures of wage discrimination

It is important to be aware that neither the methodologies based on conditional wage distribution functions nor those using quantile regressions consider how to weight the different levels of discrimination estimated throughout the wage range. Implicitly, they avoid the construction of a single aggregated indicator, which makes it difficult to compare discrimination levels between distributions.[7]

To provide measurements of discrimination at different quantiles without any aggregation criterion implies solving the judgements issue in a trivial way: no aggregation is undertaken and therefore no value judgements are incorporated.[8] However, we should not forget that, in the distribution literature, the Lorenz dominance criterion aggregates income levels in order to compare different income distributions in terms of inequality. In fact, it does so under a minimum number of value judgements on

[5] Some recent works that suffer this problem within the literature of the analysis of gender wage discrimination are Albrecht, Björklund and Vroman (2003) and Bonjour and Gerfin (2001).

[6] Note that the decomposition of wage discrimination using quantile regressions does not suffer from this problem given that it quantifies the level of discrimination experienced by females situated at different wage quantiles and does not evaluate the wage difference between them and those that occupy the same position in the non-discriminatory distribution. Dolado and Llorens (2004) avoid the construction of the counterfactual wage distribution, which is why their work is not affected by this problem, even though they follow Albrecht, Björklund and Vroman (2003).

[7] Apart from the trivial case in which a given wage distribution presents more discrimination in all estimated quantiles.

[8] As maintained by Gardeazábal and Ugidos (2004) in their introductory section.

which there has been an agreement.[9] This adds robustness but incompleteness to the orderings. And it is precisely in those cases in which Lorenz criterion cannot order functions, when complete inequality indices (Gini, Theil or Atkinson index) are most interesting. The latter incorporate a larger number of value judgements but allow us to undertake slightly more delicate orderings. Often, the results offered by this battery of indices do not coincide, but differences are not at all random. They agree with the normative properties of each of them. A deep analysis of these permits us the best comprehension of the analysed phenomenon.

Jenkins' (1994) approach advances in this direction and proposes discrimination measures that allow for the aggregation of wage gaps.[10] Our proposal extends his approach incorporating some improvements. We propose a normative framework in which to insert discrimination measurement following the literature on deprivation.

3. NORMATIVE DISCRIMINATION MEASURES

So far we have shown that, firstly, when analysing discrimination we should focus on the "experience of each individual". Given the bi-dimensional nature of this information, summarised by $(\hat{y}_{mi}, \hat{r}_{mi})$, any measure which tries to quantify it should be written as a function of $(\hat{r}_{mi} - \hat{y}_{mi})$, rather than as a function of $\hat{r}_{mi}$ and $\hat{y}_{mi}$ taken separately. Secondly, we need to aggregate these individual experiences. This implies taking value judgements into account, and these are, necessarily, of a subjective nature. Is this a problem? Not if we accept that discrimination is a *bad thing* in the same way that are poverty or the duration of unemployment. Hence the question is: what properties should a measure of discrimination satisfy? We propose that the properties the literature on economic poverty has widely accepted as satisfactory requirements for any poverty measure, are also adequate in the case of the study of wage discrimination.

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[9] Basically resumed in two axioms: *symmetry* (or *anonymity*) and the *Pigou-Dalton Principle of Transfers*.

[10] Surprisingly, few papers have followed Jenkins' (1994) approach. We only know of the empirical works of Denny, Harmon and Roche (2000), Makepeace, Paci, Joshi and Dolton (1998), Hansen and Wahlberg (2001) and Ullibarri (2003). In all these works the indices are used just as proposed by Jenkins (1994). In Favaro y Magrini (2003), differently from the rest, we find some criticisms to Jenkins' approach and authors propose the estimation of bivariant density functions as an alternative. In our opinion this is not an alternative to Jenkins' techniques but a useful descriptive tool previous to the deeper distributive analysis of discrimination we present here.

3.1 Normative properties of discrimination indices

Consider two vectors of wage gaps, $\boldsymbol{x_m}$ and $\boldsymbol{x'_m}$, where $x_m = (\hat{r}_{m_1} - \hat{y}_{m_1}, ..., \hat{r}_{m_n} - \hat{y}_{m_n})$, and $x'_m = (\hat{r}'_{m_1} - \hat{y}'_{m_1}, ..., \hat{r}'_{m_s} - \hat{y}'_{m_s})$, n and s being respectively the total number of female workers in each distribution. $d(\boldsymbol{x_m})$ represents the level of discrimination which corresponds to distribution $\boldsymbol{x_m}$ for a given measure d. The minimal set of normative properties or axioms that $d(.)$ should satisfy are the following:

1) *Continuity Axiom*. $d(\boldsymbol{x_m})$ must be a continuous function for any vector of wage gaps of its domain, $\boldsymbol{x_m}$.

2) *Focus Axiom*. If we can obtain $\boldsymbol{x'_m}$ from $\boldsymbol{x_m}$ by rises in wages of non-discriminated women, then $d(\boldsymbol{x'_m}) = d(\boldsymbol{x_m})$.[11]

3) *Symmetry* (or *Anonymity) Axiom*. If $\boldsymbol{x'_m}$ can be obtained from $\boldsymbol{x_m}$ by a finite sequence of permutations of individual wage gaps, then $d(\boldsymbol{x'_m}) = d(\boldsymbol{x_m})$.

4) *Replication Invariance Axiom*. If we can obtain $\boldsymbol{x'_m}$ from $\boldsymbol{x_m}$ by replications of the population, then $d(\boldsymbol{x'_m}) = d(\boldsymbol{x_m})$.

5) *(Weak) Monotonicity Axiom*. If $\boldsymbol{x'_m}$ can be obtained from $\boldsymbol{x_m}$ by increasing the discrimination level of a woman, then $d(\boldsymbol{x'_m}) > d(\boldsymbol{x_m})$.

6) *(Weak) Transfer Axiom*. If we can obtain $\boldsymbol{x'_m}$ from $\boldsymbol{x_m}$ by a sequence of "regressive transfers" between two discriminated female workers, so that the one with the highest discrimination suffers an increase in her wage gap equal to the decrease experienced by the other, then $d(\boldsymbol{x'_m}) > d(\boldsymbol{x_m})$.

[11] The existence of female workers with $\hat{y}_i \geq \hat{r}_i$, should not be used to balance discrimination suffered by the rest. In the same way, within the literature on poverty measurement an increase in non-poor income does not change the poverty level (keeping the same poverty line). The analysis of non-discriminated women is also interesting but is a different topic. Note that our approach also allows for the analysis of male discrimination using female wage structure as a reference.

The *Continuity Axiom* is a reasonable property for any index in order to guarantee that small changes in wage gaps do not lead to large changes in discrimination levels. The *Focus Axiom* requires the index to be dependent on the distribution of discriminated women while disregarding completely the wage level of the rest of female workers. This does not mean that measures verifying this axiom are necessarily independent of the existence of women with wage advantages with respect to male workers,[12] but it does require that these salary advantages are not taken into account when measuring aggregate discrimination.[13]

The *Symmetry Axiom* guarantees that the index does not favour any particular woman. The *Replication Invariance Axiom* is a technical property that allows for comparisons between distributions of different size. The two other final axioms lead to two basic properties. The *Monotonicity Axiom* refers to discrimination intensity, so that a worsening in the position of a discriminated woman yields a higher level of aggregate discrimination. And, finally, the *Transfer Axiom* implies that a higher inequality level between discriminated women, in terms of their discrimination sharing, leads to an increase in the discrimination index.

Accepting the axioms above, we will be able to construct discrimination profiles by accumulating individual wage gaps and develop some dominance criteria to rank wage distributions according to their discrimination level. Subsequently we could make a correspondence between these rankings and those obtained by using complete discrimination indices that also satisfy these properties. This is the case in the inequality and poverty field, where there are valuable theorems that establish a relationship between the income distribution ranking obtained by Lorenz or TIP's dominance criteria and those obtained by complete inequality and poverty indices compatible with those criteria. Thus, by using a minimal set of judgements, summarised in the above properties, we will be able to identify particular empirical cases where the discrimination distribution ranking is independent of the index chosen, since all indices

[12] In fact, the share of these women over total female workers will be taken into account in all indices that verify *continuity, monotonicity* and *replication invariance axioms* (see Zheng (1997) for the poverty case).
[13] This is similar to considering that the existence of famous Gypsy musicians or Afro-American sportsmen from discriminated groups should not offset the inferior position of most individuals in these groups.

yield the same result. This makes our analysis of discrimination significantly more robust.

This line of research was opened by Jenkins (1994) when he used the Inverse Generalised Lorenz Curve (IGLC) in the discrimination field, and defined discrimination indices consistent with its dominance criterion.[14] Later, in the deprivation field, Shorrocks (1998) generalised these relationships in the continuous case and summarised previous results obtained by different authors. In what follows, we extend this analysis and propose the use of Discrimination Curves and discrimination indices that will be defined so as to satisfy the above axioms.

3.2 Dominance relations between Discrimination Curves

Let us define $g(x_m)$ to be the vector of individual wage discrimination, which corresponds to the wage gap $x_m = (\hat{r}_{m_1} - \hat{y}_{m_1}, \hat{r}_{m_2} - \hat{y}_{m_2}, ..., \hat{r}_{m_n} - \hat{y}_{m_n})$:

$$g_i(x_m) = \max\left\{(\hat{r}_{m_i} - \hat{y}_{m_i}), 0\right\}$$

The Discrimination Curve represents for each $0 \le p \le 1$ the sum of the first 100**p* per cent of $g(x_m)$ values divided by the total number of female workers, *n*, once these have been ranked from a higher to a lower wage discrimination level. Hence, $g(x_m) = (g_1, g_2, ..., g_n)$ satisfies that $g_1 \ge g_2 \ge ... \ge g_n$, and for each value of *p* = *k*/*n* the curve can be written as:

$$D(g; p) = \sum_{i=1}^{k} \frac{g_i}{n}$$

where *k* is any integer number such that *k*<=*n*.[15]

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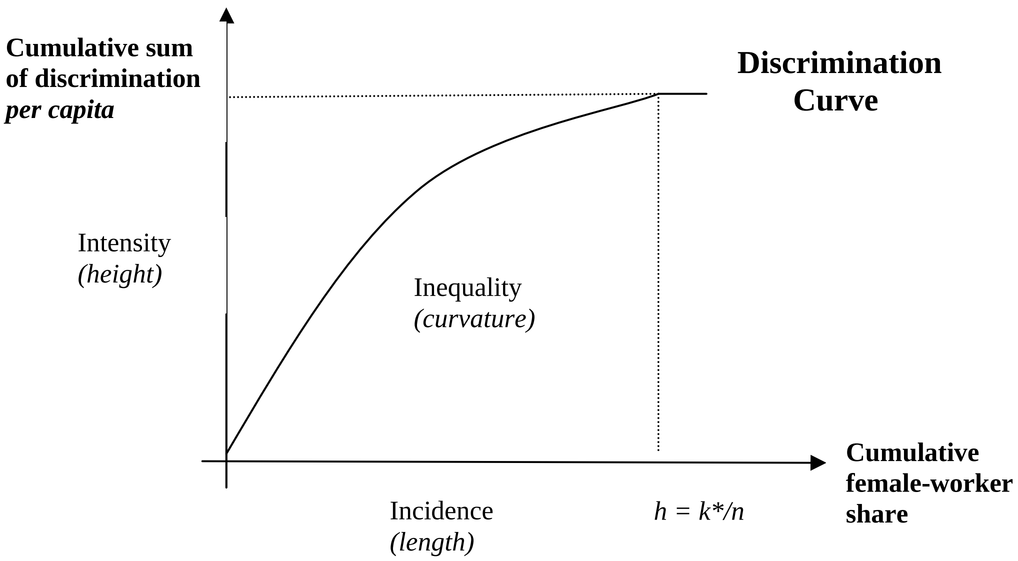
[14] This curve represents the per capita cumulative sum of wage gaps, on absolute values, for each cumulative proportion of women, once they have been ranked from higher to lower absolute wage gap. Note that Jenkins (1994), when defining the IGLC on absolute values of $\boldsymbol{x_m}$, does not impose the *focus axiom*. However, as it has been shown, it seems reasonable to redefine the variable, the dominance criterion and the indices he proposes taking that axiom into account.

[15] The Discrimination Curve is the IGLC defined for $g(x_m)$, rather than for absolute values of wage gaps, as in Jenkins (1994). The latter implies, counter-intuitively, considering positive and negative wage gaps as equivalents.

D(g;p) accumulates individual discrimination levels, from higher to lower discrimination, divided by *n*. As shown in Graph 3,[16] *D* is a positive, increasing and concave function; where *D(g;0)* = 0, *D(g;1)* = $\bar{g}$, and takes a constant value when we consider the last discriminated woman, k^*.

Graph 3. Discrimination Curve



The shape of the above curve provides us with useful information. First, it shows the *incidence* of discrimination so that to identify the proportion of discriminated women we need to know only the percentile where the curve becomes a horizontal line, $h=k^*/n$. Second, it informs us about its *intensity*, since the height of the curve is the accumulated discrimination averaged by the number of female workers. Third, it also shows the *inequality* aspect of the discrimination distribution by the degree of concavity of the curve before point *h*.

Definition of dominance in discrimination. Given two discrimination vectors, g^1 y g^2, we would say that:

g^1 dominates g^2 in a discriminatory sense if

$$g^1 \neq g^2 \text{ and } D(g^1;p) \leq D(g^2;p) \text{ for any } p \in [0,1]$$

[16] This is an adaptation of Figure 1 in Jenkins y Lambert (1997), where the properties of the TIP curves

It is straightforward then to show that this dominance criterion is closely linked to the six properties mentioned above.[17] Thus, we can establish a relationship between dominance in the discriminatory sense and the set of aggregate indices, $d^*(x_m)$, that satisfy in $g(x_m)$ the *continuity, focus, monotonicity, symmetry, transfer* and *replication invariance axioms*.

Theorem:[18]
For any pair of discrimination distributions, g^1 and g^2 , it follows that,

$$g^1 \text{ dominates } g^2 \text{ in a discriminatory sense}$$
$$\Leftrightarrow$$
$$d(x_m^1) < d(x_m^2) \text{ for any } d(\cdot) \in d^*$$

Hence, a higher discrimination curve leads, unambiguously, to a higher discrimination level.[19]

3.3 Complete indices consistent with dominance discrimination

Since the dominance criterion is not always able to give us conclusive results in empirical applications (the estimated discrimination curves can cross) it is interesting to consider the use of some of the indices belonging to d^*. We are interested in those that satisfy both the axioms above and any other property that may be of special interest for wide empirical analysis, such as *decomposability*.

are shown to measure aggregate poverty.

[17] See Del Río, Gradín and Cantó (2004).

[18] This result was first shown in Shorrocks (1993), where it was used to study the duration of unemployment, and in Jenkins and Lambert (1993), in the poverty field. This work established the basis for later results on TIP curves (Jenkins y Lambert (1997, 1998)). The continuous case is shown in Shorrocks (1998). Jenkins (1994) first used this approach in the wage discrimination field, where he defined wage discrimination as the difference, in absolute terms, between the wages estimated with and without discrimination

[19] Also this result makes it possible to quantify the differences in discrimination between two wage distributions without using complete indices. This stems from Theorems 4 and 5 in Jenkins and Lambert (1998). For more details see Del Río, Gradín and Cantó (2004).

Additive Decomposability. Consider a partition within $\boldsymbol{x_m}$, where $n_1 + n_2 + ... + n_J = n$ are the sizes of J subpopulations $\boldsymbol{x_m}^{(1)}$, $\boldsymbol{x_m}^{(2)}$, ..., $\boldsymbol{x_m}^{(J)}$. A discrimination index d is said to be additively decomposable if:

$$d(x_m) = \sum_{j=1}^{J} \left(\frac{n_j}{n} \right) d(x_m^{(j)}) .$$

This property suggests that it may be desirable to decompose overall discrimination as the weighted sum of subpopulation discrimination levels. However, this is not a widely accepted criterion in the poverty field if, for example, we consider that the poverty level in a group cannot be independent of that in other groups. Despite this serious criticism, the above property is clearly very helpful in most empirical applications, since it allows us to measure the contribution of each population group to the total level of detected discrimination. This means that we can study discrimination for different female characteristics and thus not only classify individuals by earnings (as in the quantile estimations mentioned above) but also by any other variable, such as education level, age or geographical location.

Jenkins (1994) proposed the use of different *families* of aggregate discrimination indices. If they were conveniently defined over $\boldsymbol{x_m}$, instead of $|\hat{r}_m - \hat{y}_m|$ as initially proposed, the main difference of Jenkins' approach with respect to our proposal would be the *transfer axiom*. Jenkins shows a preference for the use of indices that do not satisfy this axiom.[20] In fact, the family of decomposable indices, J_α, that he uses in his empirical analysis is a concave function that depends on the relative individual discrimination level (with respect to the average wage). The concavity of this index guarantees that it takes values between 0 and 1, which is a good property. However, this also means that the more evenly discrimination is distributed, the higher will be the value of the index. And reciprocally: given a constant aggregate wage gap, the more discrimination is focused on fewer women the lower will be the discrimination level. It follows that evenness in the distribution of discrimination is being penalised. Jenkins here is not consistent with his initial approach about the individual nature of discrimination: the relevance of its distribution and its similarities with economic

[20] Even though he offers theoretical results for both cases depending on the sign and value of a parameter.

poverty clearly make the *transfer axiom* a desirable property for any discrimination index to satisfy.

Taking into account all the above, we consider that it is not necessary to define new discrimination indices, as Jenkins suggests, but only to make good use of those with the best normative properties within the poverty literature.[21] Therefore, the family indices proposed by Foster, Greer y Thorbecke (1984), for values of their poverty aversion parameter higher than 1, satisfy our requirements. If we adapt their index to measure (absolute) discrimination we can write a discrimination index such that:

$$d_\alpha(x_m) = \left(\frac{1}{n}\right) \sum_{i=1}^{k^*} (x_{m_i})^\alpha \quad , \quad \alpha > 1$$

where k^* denotes again the number of discriminated female workers and α is the discrimination aversion parameter. It is well known that $d_\alpha \in d^*$, and also that it is additively decomposable.[22]

3.4 Absolute versus relative discrimination

An additional issue in the measurement of discrimination is whether to use a relative rather than an absolute approach. In order to do this we need to define new indices, dr_α , which would be a function of the wage gap vector normalised with respect to some average wage, for example:[23]

$$dr_\alpha(x_m / \bar{\hat{r}}_m) = \left(\frac{1}{n}\right) \sum_{i=1}^{k^*} (x_{m_i} / \bar{\hat{r}}_m)^\alpha$$

Another interesting possibility consists in normalising each female wage gap individually, by dividing it by her earnings without discrimination. This implies that the

[21] Zheng (1997 and 2000) offers a survey of the main poverty indices and also of the theorems which link those indices with poverty orderings based on deprivation profiles.
[22] It would be interesting to measure discrimination adapting our approach to the use of different poverty indices which satisfy other normative properties such as those proposed by Sen (1976) or Hagenaars (1987). The latter would allow us to measure discrimination as the social welfare loss it causes.
[23] Another possibility would be to use the mean predicted wage with discrimination, $\bar{\hat{y}}_m$, or the mean observed wage, $\bar{y}_m$.

critical point is no longer the average wage but, instead, the highest discrimination level that each woman could suffer: [24]

$$dr_{\alpha}(v_{m_i}) = dr_{\alpha}\left(\frac{\hat{r}_{m_i} - \hat{y}_{m_i}}{\hat{r}_{m_i}}\right) = \left(\frac{1}{n}\right) \sum_{i=1}^{k*}(v_{m_i})^{\alpha}$$

In order to guarantee that these indices satisfy the same properties as $d_{\alpha}(x_m)$, we need to redefine the discrimination curves on the normalised discrimination vector, reformulating the dominance criterion and the theorem in a consistent way.[25]

4. AN EMPIRICAL ANALYSIS: THE CASE OF SPAIN

In this section, our goal is to show the advantages of our approach. We will compare aggregate discrimination levels for Spanish labour market data obtained using OLS and Quantile Regressions (QR) for males and females. Coefficients are reported in Table A1 in the Appendix. [26]

The variable to be explained is the logarithm of hourly wage, and explanatory variables are those usually included in the related literature and available in the database: tenure, experience, education, region, type of contract, occupation, firm size, type of collective agreement, firm-ownership and type of reference market (international, national or local).[27] Wage regression results are shown to be roughly consistent with other previous empirical analyses.

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[24] The role played by $\hat{r}_{m_i}$ in this kind of normalisation is similar to that of the poverty line in the deprivation literature. Hence, by dividing the individual wage gap by $\hat{r}_{m_i}$, we do something similar to what is done in the poverty literature when constructing relative poverty gaps by using individual poverty lines for each household (depending on its size, composition, location,...).

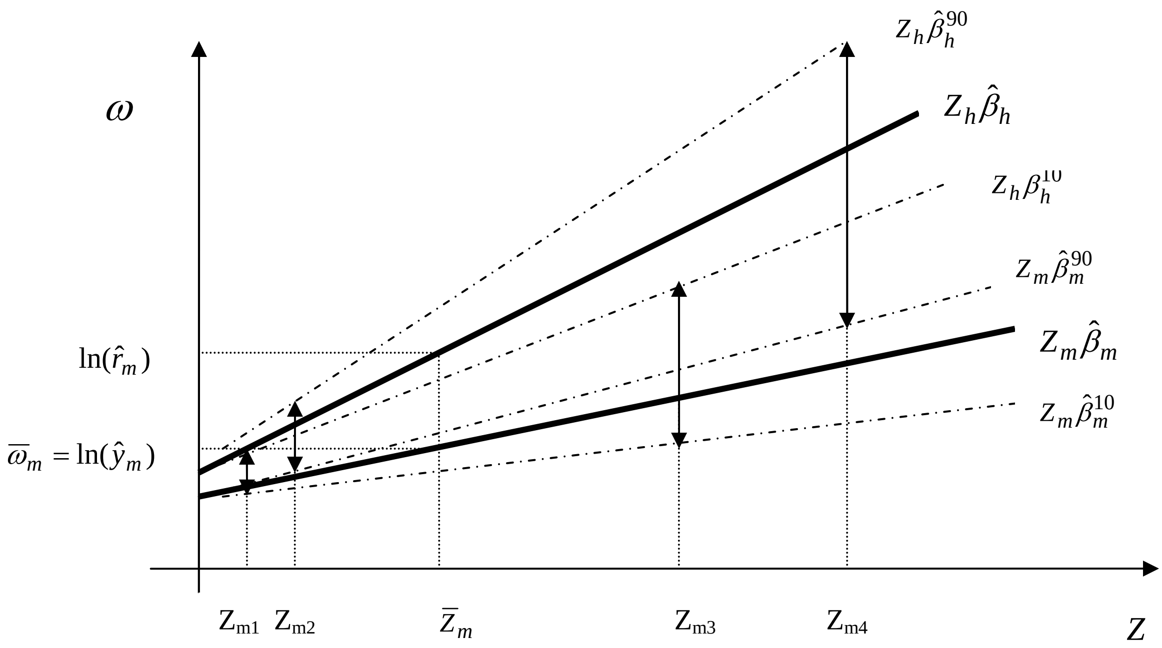
[25] This point was missed by Jenkins (1994) and implies an inconsistency in the interpretation of Results 1 and 2 of his work when relating them to J_{α} and R_v indices. For more details see Del Río, Gradín and Cantó (2004).

[26] Data come from the *Encuesta de Estructura Salarial* (Survey of Wage Structure) undertaken by the Instituto Nacional de Estadística (INE) in 1995. See Del Río, Gradín and Cantó (2004) for more details.

[27] It was not possible, however, to control for other relevant workers' personal characteristics such as marital status or the presence of children in the household. Furthermore, this database only contains working women and does not allow controlling for *selection bias.*

We construct wage distributions for working women estimated with and without discrimination. These estimates are denoted respectively by $\hat{y}_m$ and $\hat{r}_m$ in the OLS case, and $\hat{y}_m^q$ and $\hat{r}_m^q$ in the quantile case.[28] In the latter case, $\hat{y}_m^q$ was calculated by attaching to each working woman those coefficients estimated in the female quantile regression which minimises her individual residual, q_i^*. $\hat{r}_m^q$ was computed for each woman using the *male* wage structure at quantile q_i^*. In this way, what we are actually doing for each woman is selecting her predicted wage, $\hat{y}_{m_i}^{q*}$, as the closest to her actual wage y_{m_i} and comparing it with a male wage, $\hat{r}_{m_i}^{q*}$, estimated for a hypothetical man with her characteristics and situated in the same relative ranking within the conditional male wage distribution (as shown in Graph 4). [29]

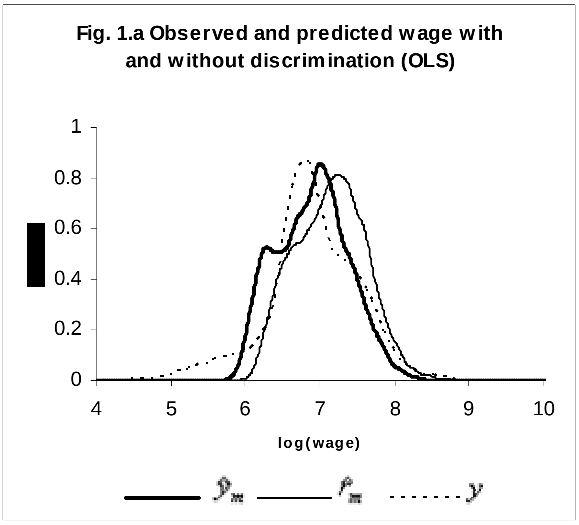
Graph 4. Wage discrimination using Quantile Regressions

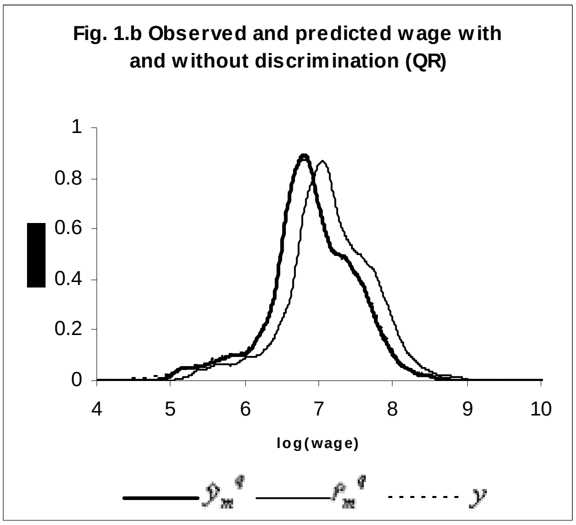


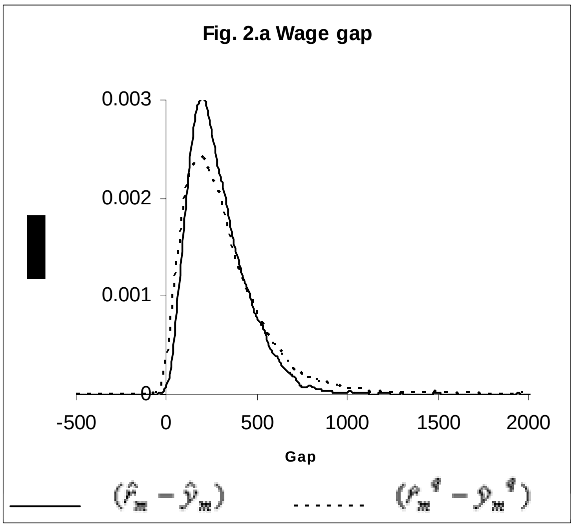
[28] We compute quantile regressions in ten different points of the distribution (the mean quantile within each decile: i.e. 5th, 15th, 25th, …., 95th).

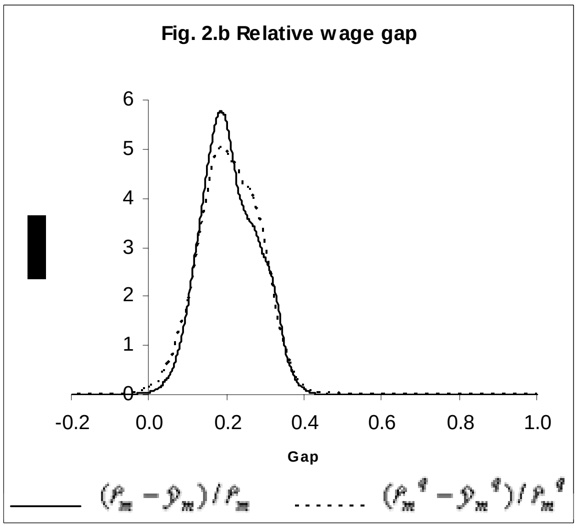
[29] Obviously, this is an *ad hoc* use of predicted wages that might be forcing the interpretation of this type of estimates, but the purpose here is to explore to what extent OLS and QR differ, not only because they make estimates at different points in the distribution, but because they also yield different aggregate levels of discrimination.

Descriptive statistics for wages and gender gaps estimated with both models are reported in Table A2, in the Appendix, while the corresponding non-parametric *kernel* densities are depicted in Figures 1a to 2b. Observed wages result in a more accurate fit using QR, especially evident in the tails, and thus showing a greater dispersion than OLS. Further, QR presents a greater dispersion of wage gap density estimations in the absolute case, but not so much as when normalised by $\hat{r}_{m_i}$.









Absolute and normalised discrimination curves are depicted in Figures 3a and 3b. OLS wage distribution dominates QR in discrimination. A consequence is that QR discrimination is always larger for all discrimination indices fulfilling the axioms proposed (in both absolute and relative cases).[30] We can check this just by looking at discrimination measures reported in Table 1.[31]

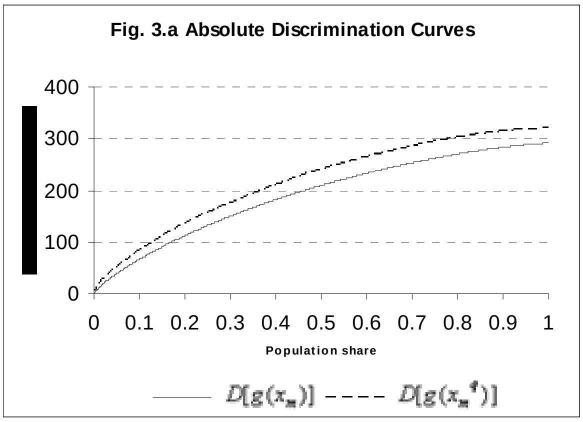


Fig. 3.a Absolute Discrimination Curves

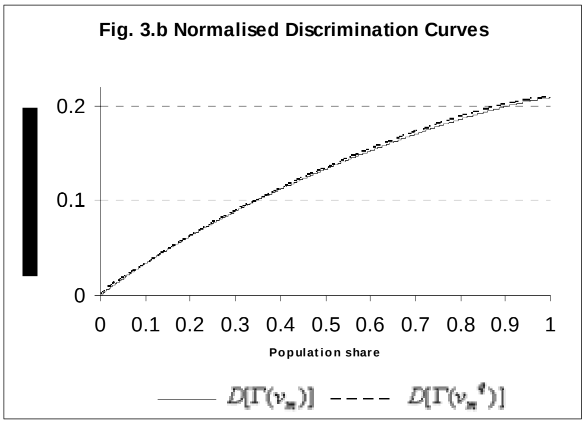


Fig. 3.b Normalised Discrimination Curves

Table 1. Indices of Discrimination

	Absolute OLS	QR		Normalised OLS	QR
h	0.9988	0.9962	***h***	0.9988	0.9962
d₁	291.22	320.82	***dr₁***	0.208	0.209
d₂	116,000	166,000	***dr₂***	0.049	0.050
d₃	6.E+07	1.E+08	***dr₃***	0.012	0.013
d₄	5.E+10	2.E+11	***dr₄***	0.003	0.004

In order to analyse the distributive aspects we compare discrimination curves estimated separately for each decile in Figures 4a and 4b. Absolute discrimination increases as wages grow in both OLS and QR. Relative discrimination, however, shows a more ambiguous pattern due to crosses between different decile curves.[32] In any case, discrimination is larger at the bottom than at the top.

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[30] Notice that our notion of *relative discrimination* is based on the ratio of the estimated discrimination to the wage without discrimination, not to the total wage gap as is usual in the literature. This should be taken into account when comparing our results with previous evidence.

[31] In Table 1 we present two additional indices despite the fact that they do not verify all the proposed axioms: the head-count ratio of discriminated women, *h*, which provides information on the *incidence* of discrimination among working women (being larger than 99% in both cases), and *d* and *dr* indices for a discrimination aversion level equal to one, indicating the amount of money that one should transfer to discriminated women in order to remove discrimination (in absolute and relative terms respectively).

[32] Normalised discrimination curves can be found in Del Río, Gradín and Cantó (2004).

Fig. 4a. Absolute Discrimination Curves by deciles OLS

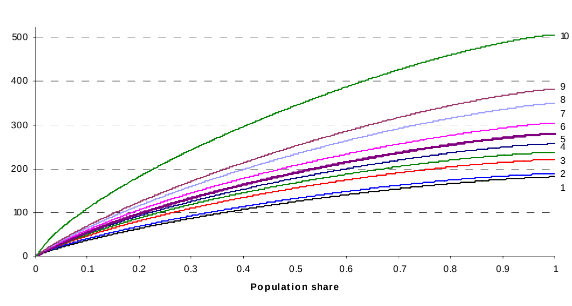
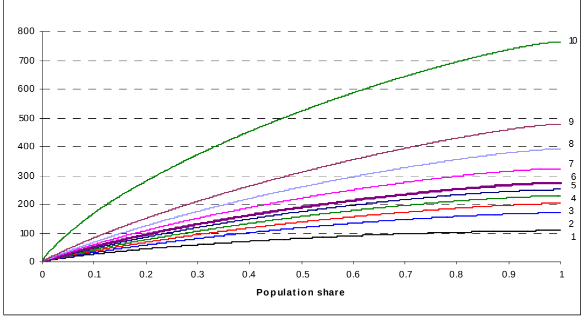


Fig. 4b. Absolute Discrimination Curves by deciles QR



In the relative case, we are interested in a more explicit, even if less robust, answer and thus we propose the use of additively decomposable indices of relative discrimination.

Figures 5 and 6 display, for dr_2, the ratio of within-group discrimination to total discrimination estimated for each decile (based on observed wage) and education level. A ratio value above (below) one indicates a level of discrimination larger (smaller) than average. When we break down our female workers' sample into wage deciles, both estimations show a similar pattern: the largest relative discrimination is found in the first decile, while for higher deciles discrimination decreases slightly (with the exception of the last decile). On the contrary, separating by education levels, relative discrimination is higher than average for women without studies and lower for those with higher studies.

Fig. 5 Discrimination by deciles: dr_2 ratio (average = 1)

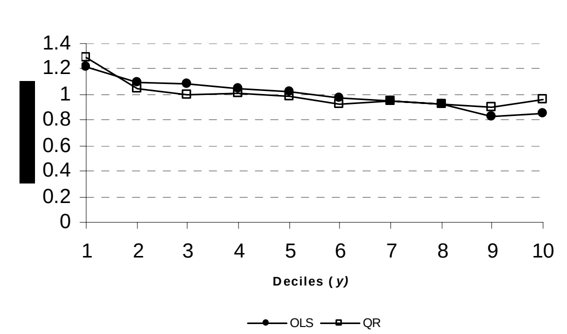
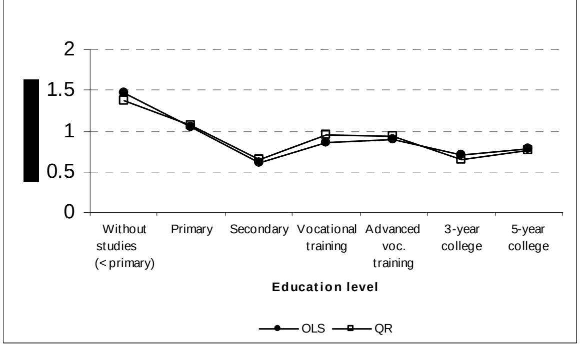


Fig. 6 Discrimination by education level: dr_2 ratio (average = 1)



Furthermore, we break the sample into those holding a university degree and the rest of females, following Dolado and Llorens (2004). Figures 7a and 7b present discrimination patterns by deciles for these two groups. The most important group of females (without university studies) resembles the general pattern except for in the last decile. However, discrimination increases with the wage level among those females with a university degree. The increase is sharper for the last decile when using QR. Thus, among top-wage female earners, more skilled women are facing the largest relative discrimination, roughly similar to the opposite group: low-wage unskilled women.[33]

Fig. 7a Discriminationby deciles (non-university degree): dr_2 ratio (average = 1)

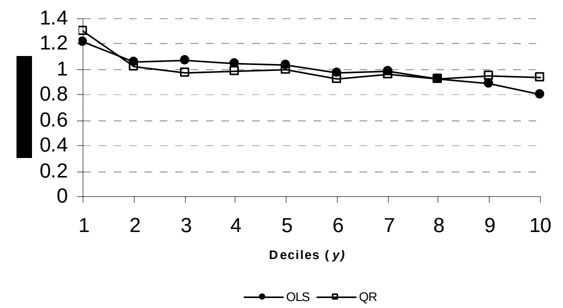
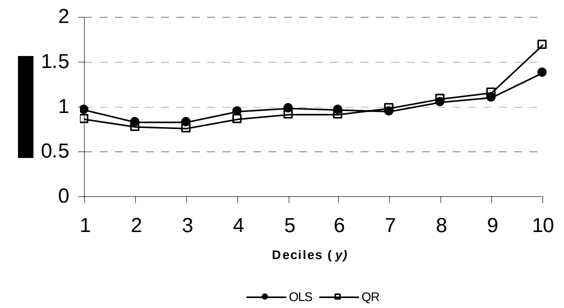


Fig. 7b Discrimination by deciles (university degree): dr_2 ratio (average = 1)



5. CONCLUSIONS

In this paper we have detailed the advantages of analysing wage discrimination from a distributive point of view, considering each individual discriminatory experience. We have exposed the limitations of using the classic approaches to the measurement of discrimination based on the analysis of the mean discriminatory experience and also of those that use some recent distributive methodologies based on quantile regressions and counterfactual wage distributions. Our theoretical contributions are: 1) to underline the imprecise measurement of discrimination using counterfactual functions: this is related to re-orderings as we move from the original wage distribution to a hypothetical non-discriminatory one; and, most importantly, 2) to propose a new normative framework for the study of wage discrimination based on the poverty and deprivation literature. For the latter we provide a variety of improvements to Jenkins' (1994) approach to the aggregation of individual discriminatory experiences by adding to its consistency and normative power.

[33] This result can be extended to other indices due to dominance by deciles in normalised discrimination curves.

The empirical exercise using Spanish data allows us to present the differences between OLS and Quantile Regressions in the estimation of female individual discriminatory experiences. This exercise shows that quantile regressions reveal a significantly higher level of aggregate discrimination compared to that detected using classical estimation techniques on the mean. Therefore, the choice between OLS and Quantile Regressions is all but innocuous from an aggregate point of view. Nevertheless both methods raise roughly similar discrimination patterns throughout the wage range. It seems clear that absolute discrimination increases with observed wages, while in relative terms this result is not robust. Only females with very low wages and, at the other extreme of the distribution, those holding a University degree and earning the highest salaries, register a relative discrimination significantly above that of the rest.

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APPENDIX

Table A1. OLS and Quantile regression estimates for hourly wage in logarithms

	Males						Females					
	OLS	Percentiles					OLS	Percentiles				
		5	25	45	75	95		5	25	45	75	95
Tenure	0.040	0.054	0.036	0.029	0.024	0.017	0.028	0.041	0.025	0.021	0.015	0.011
Tenure^2	-0.001	-0.001	-0.001	-0.001	0.000	0.000	-0.001	-0.001	0.000	0.000	0.000	0.000
Experience	0.024	0.014	0.017	0.020	0.024	0.028	0.032	0.025	0.027	0.029	0.033	0.037
Experience^2	-0.0003	-0.0002	-0.0002	-0.0003	-0.0003	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005
Education [reference: Without studies or less than primary]												
Primary	0.065	0.014 *	0.047	0.044	0.065	0.089	0.046	0.041	0.024	0.041	0.054	0.072
Secondary	0.275	0.185	0.225	0.236	0.282	0.353	0.234	0.182	0.181	0.220	0.254	0.324
Vocational training	0.143	0.078	0.109	0.121	0.137	0.145	0.135	0.125	0.108	0.133	0.150	0.159
Advanced voc. training	0.234	0.171	0.196	0.197	0.225	0.322	0.243	0.206	0.209	0.238	0.261	0.280
3-year college	0.380	0.241	0.310	0.357	0.414	0.443	0.379	0.302	0.332	0.361	0.382	0.430
5-year college	0.570	0.343	0.474	0.523	0.625	0.703	0.582	0.439	0.503	0.561	0.610	0.679
Type of contract [reference: Fixed term contract]												
Indefinite contract	0.257	0.710	0.408	0.206	0.122	0.154	0.286	0.793	0.405	0.200	0.160	0.169
Occupation [reference: Non-qualified workers (9)]												
Managers	0.664	0.456	0.624	0.658	0.738	0.883	0.742	0.509	0.651	0.732	0.849	0.991
Professionals	0.540	0.503	0.553	0.523	0.516	0.616	0.495	0.432	0.487	0.488	0.512	0.614
Technicians	0.430	0.380	0.406	0.404	0.431	0.520	0.364	0.271	0.316	0.349	0.414	0.522
Clerks	0.219	0.250	0.228	0.206	0.210	0.257	0.191	0.184	0.168	0.183	0.208	0.267
Qualified (services)	0.149	0.184	0.172	0.144	0.112	0.111	0.063	0.095	0.070	0.058	0.049	0.122
Qualified (industry)	0.045	0.046 *	0.019 *	0.018 *	0.045	0.079	0.138	0.160	0.134	0.124	0.125	0.167
Operators	0.017 *	0.005 *	-0.003 *	-0.011 *	0.025	0.060	0.128	0.131	0.123	0.123	0.130	0.151
Size of the firm [reference: 10-19 workers]												
20-49 workers	0.010 *	0.012 *	0.008 *	0.019	0.022	0.041	0.063	0.059	0.046	0.056	0.085	0.092
50-99 workers	0.044	0.030 *	0.019 *	0.061	0.084	0.106	0.136	0.111	0.131	0.137	0.156	0.158
100-199 workers	0.116	0.074	0.100	0.128	0.135	0.176	0.179	0.152	0.191	0.189	0.195	0.196
> 200 workers	0.165	0.139	0.160	0.197	0.216	0.256	0.276	0.281	0.302	0.286	0.289	0.262
Type of labour agreement [reference: Firm labour agreement]												
National labour agreement	-0.072	-0.050	-0.104	-0.109	-0.105	-0.037	-0.066	-0.074	-0.087	-0.088	-0.074	-0.049
Sector or provincial agreement	-0.096	-0.063	-0.103	-0.122	-0.127	-0.071	-0.067	-0.055	-0.088	-0.094	-0.086	-0.061
Type of Sector [reference: Private sector]												
Public sector	0.140	0.243	0.032 *	0.076	0.210	0.144	0.027	0.167	0.061	0.049	-0.019 *	-0.061
Market [reference: Foreign market]												
Local-regional market	-0.057	-0.116	-0.066	-0.049	-0.046	-0.034	-0.016	-0.015 *	-0.019	-0.006 *	-0.007 *	-0.007 *
National market	-0.012 *	-0.030 *	-0.014 *	0.002 *	0.003 *	0.011 *	0.018	-0.023	0.007 *	0.017	0.030	0.060
Constant	5.938	5.101	5.783	6.110	6.330	6.421	6.009	5.073	5.804	6.147	6.379	6.580
R^2 or Pseudo-R^2	0.59	0.45	0.35	0.37	0.43	0.43	0.62	0.46	0.38	0.40	0.42	0.44
Observations				27,085						100,208		

* = coefficient is not significant at 10%. Coefficents for Regions omitted. OLS variances computed using White estimator.
Quantile regressions were performed also at percentiles 15, 35, 55, 65 and 85, not displayed for simplicity.

Table A2. Summary statistics: average and dispersion

	Average	Theil (0)	Theil (1)	Theil (2)	Gini
Wage					
Observed y	1,188	0.182	0.175	0.210	0.320
Predicted by OLS					
$\hat{y}_m$	1,113	0.116	0.116	0.128	0.269
$\hat{r}_m$	1,404	0.111	0.110	0.122	0.262
Predicted by QR					
$\hat{y}_m^q$	1,177	0.166	0.160	0.185	0.308
$\hat{r}_m^q$	1,496	0.167	0.163	0.193	0.310
Discrimination gap					
OLS					
$(\hat{r}_m - \hat{y}_m)$	291.2	0.176	0.163	0.186	0.315
$(\hat{r}_m - \hat{y}_m)/\hat{r}_m$	0.208	0.070	0.061	0.060	0.196
QR					
$(\hat{r}_m^q - \hat{y}_m^q)$	319.5	0.276	0.248	0.312	0.383
$(\hat{r}_m^q - \hat{y}_m^q)/\hat{r}_m^q$	0.209	0.087	0.071	0.069	0.209