ESTUDIOS SOBRE LA ECONOMIA ESPAÑOLA

Measuring the gender gap at different quantiles of the wages distribution

Javier Gardeazabal
Arantza Ugidos

EEE 108

June 2001

FEDEA
Fundación de Estudios de Economía Aplicada

http://www.fedea.es/hojas/publicado.html

Measuring the gender gap at di¤erent quantiles of the wage distribution.

Javier Gardeazabal and Arantza Ugidos[¤yz]
Universidad del País Vasco

Abstract

In this paper we study gender wage discrimination. We use quantile regression to study the e¤ect of individual characteristics on wages at various points of the distribution of wages. A simple extension of Oaxaca's mean gender wage gap decomposition is developed. We propose two measures of discrimination, one in absolute terms and the other in relative terms. Using the Spanish sample of the Survey of Wage Structure we …nd that returns to characteristics vary across quantiles and gender. Discrimination measured in absolute terms increases as we move to higher quantiles. However, discrimination measured as a fraction of the gender wage gap decreases as one moves from low to higher quantiles.

[¤] Javier Gardeazabal, Departamento de Fundamentos del Análisis Económico, Universidad del País Vasco, Avda. Lehendakari Aguirre 83, 48015 Bilbao, Spain, E-mail: jepgamaj@bs.ehu.es

[y] Arantza Ugidos, Departamento de Fundamentos del Análisis Económico, Universidad del País Vasco, Avda. Lehendakari Aguirre 83, 48015 Bilbao, Spain, E-mail: jepugola@bs.ehu.es

[z] We would like to thank Alberto Abadie, Teo Pérez Amaral and seminar participants at Universidad Complutense de Madrid and Universidad de Valencia. Financial support from The Basque Government ######## and The Spanish Ministry of Education ########## is gratefully acknowledged.

1 Introduction

The approach most widely used in measuring the extent of gender wage discrimination is based on the human capital theory of wage determination. According to human capital theory wages are tied to productivity. In a non-discriminatory environment, the observed male-female wage di¤erentials should be due to di¤erences in productivity between men and women. Gender wage discrimination takes place when equally productive workers are paid di¤erent wage rates. When there is discrimination, male-female wage di¤erentials cannot be explained only in terms of di¤erences in productivity.

Since productivity is not observed by researchers, measures of discrimination usually adjust for all measurable characteristics that might be expected to a¤ect productivity.[1] While there is a proli…c literature on gender wage di¤erentials, most of these studies analyze di¤erentials in average wages between men and women. Therefore, the measures of discrimination used in the literature can be thought of as measures of discrimination at the mean of the observed distribution of wages. Although it is interesting to know how di¤erent male and female mean wages are, in this paper we also study gender wage di¤erences at other points of the distribution of wages. In this paper we investigate whether the degree of gender wage discrimination changes when we compare males and females in the bottom part of the distribution of wages or in the top part. In other words, we study whether there is more gender wage discrimination among high earners or among low earners.

In order to measure gender wage discrimination, the observed mean wage gap is typically split into two parts; the part due to di¤erences in characteristics and the part due to di¤erences in returns to these characteristics. The latter part is then used to calculate the extent of gender wage discrimination. The measures of discrimination used in the literature cannot be applied to measure discrimination at other locations of the distribution of wages. In this paper we generalize Oaxaca's measure of discrimination to any quantile of the wage distribution.[2] We propose two measures of discrimination; absolute and relative discrimination. Absolute discrimination is a direct measure of the degree of discrimination and a simple extension of Oaxaca's measure. Relative discrimination is a measure of discrimination relative to the total gender wage di¤erential at a given point of the wage distribution.

In order to construct a measure of discrimination at a given quantile it is necessary to estimate the returns to characteristics at that quantile. We use quantile regression to estimate the e¤ect of individual characteristics on

[1] See the original work by Mincer (1974) and Willis (1986) for a survey on wage determinants and human capital earnings funtions.

[2] See Oaxaca (1973).

wages, both for males and females, at various quantiles of the distribution of wages.[3] Quantile regression has previously been applied to the study of gender wage discrimination. To our knowledge there are two papers dealing with this issue. Reilly (1999) has investigated the effect of Russia's transition on gender wage gap. His findings support the idea of no change in the gender pay gap during Russia's transition. García, Hernández and López (1998) (henceforth GHL) make use of quantile regression to measure gender wage discrimination in Spain. They find an increasing gender wage gap as one moves upwards in the distribution of wages both in absolute terms and relatively to the gender wage gap.

In this paper we use the Spanish sample of the Survey of Wage Structure (SWS) of 1995 to compute both, returns to characteristics and measures of discrimination at different quantiles. Our findings suggest two main conclusions: (i) returns to characteristics vary across quantiles and gender, and (ii) as we move to higher quantiles, discrimination increases in absolute terms, but contrary to the findings of GHL, decreases relatively to unconditional gender wage gap.

The rest of the paper is organized as follows. Section 2 deals with the measurement of the gender wage gap. Section 3 outlines the typical procedure used in the literature to decompose the mean gender wage gap into differences in characteristics and differences in the returns to characteristics. Section 4 extends the previous decomposition to quantiles and proposes two measures of gender wage discrimination and also outlines a procedure to compute sample counterparts of the theoretical measures. Section 5 comments on a measure of discrimination previously used in the literature. Section 6 presents empirical evidence on gender wage discrimination at quantiles using the Spanish SWS of 1995. Finally, section 7 concludes.

2 The gender wage gap.

Gender wage differences can be due to discrimination or to differences in productivity or both. In this section we study how to measure the gender wage gap and in the next two sections how to decompose the gender wage gap into differences in characteristics and differences in returns to characteristics.

Let us denote by w_g (where $g = m; f$; where m stands for male and f for female) the (log) hourly wage, and $F(w_g)$ its distribution function. Usually

[3] Chamberlain (1994) and Buchinsky (1994, 1995, 1998) applied quantile regression to study the wage structure in the US. Pereira and Martins (2000) used the same technique to study returns to education in fifteen European countries. Abadie (1997) applied it to study the distribution of earnings in Spain.

the gender wage gap is measured as the difference between the means of the distributions, that is, $E(w_m) - E(w_f)$. This difference of the gender wage gap gives a direct and simple overall measure of the gender wage gap. However, if one is interested in measuring the gender wage gap at the bottom or the top of the distribution of wages the gender mean wage differential cannot be used. For that matter, a full array of gender quantile wage differentials is available. Denote by $w_{g\theta}$ the $\theta-$th quantile of w_g, that is, $F(w_g \leq w_{g\theta}) = \theta$. We will denote by $Q_\theta(\cdot)$ the operator such that $Q_\theta(w_g) = w_{g\theta}$. Therefore, the gender wage gap at quantile θ can be measured as $Q_\theta(w_m) - Q_\theta(w_f) = w_{m\theta} - w_{f\theta}$.

Two remarks about the gender wage gap are worth mentioning. First, even though the gender wage gap could be negative, theoretically at least, the gender wage gap is empirically positive, both at the mean and quantiles and across samples and countries. This indicates that men are paid more. Second, the gender wage gap is not an upper bound on discrimination. When women are more productive than men, but yet are discriminated, discrimination is greater than the gender wage gap.

3 Wage discrimination at the mean.

Assume that, conditional on a $(J \times 1)$ vector of characteristics, x_g, the expected value of both male and female (log) wages is linear

$$E(w_g \mid x_g) = \beta'_g x_g. \tag{1}$$

Let $u_g = w_g - E(w_g \mid x_g)$ then

$$w_g = \beta'_g x_g + u_g,$$

where $E(u_g \mid x_g) = 0$. The $j-$th element of β_g measures the return of the $j-$th characteristic on the mean of the distribution of (log) wages. Integrating over the distribution of x_g we get

$$E(w_g) = \beta'_g E(x_g).$$

Next we consider the difference between male and female unconditional mean wages

$$E(w_m) - E(w_f) = \beta'_m E(x_m) - \beta'_f E(x_f) = A_O + B_O$$

$$A_O = \left(\beta'_m - \beta'_f\right) E(x_f);$$

$$B_O = \beta'_m(E(x_m) - E(x_f)):$$

The resulting equation decomposes the mean gender wage gap in the sum of two terms. The first term, A_O; measures wage differences due to the return to characteristics, usually attributed to discrimination. This term is then used to construct a measure of gender wage discrimination. The second term, B_O; measures wage difference due to different characteristics of males and females.[4]

Oaxaca's measure of discrimination is based on the discriminatory part of the decomposition

$$D_O = \exp(A_O) - 1:$$

This measure is a measure of absolute discrimination, as D_O is insensitive to the magnitude of B_O: Oaxaca's measure is exactly the same whether male and female mean characteristics are identical, $E(x_m) = E(x_f)$; or very different.

In this paper we also consider a measure of relative discrimination

$$G_O = \frac{A_O}{A_O + B_O};$$

which measures the magnitude of gender wage differences due to returns to characteristics relative to the mean gender wage gap.

4 Wage discrimination at unconditional quantiles.

When the researcher is concerned with other location measures different from the mean, say the $\theta -$ th quantile, the same procedure outlined above can also be applied with minor differences.

Assume that, conditional on a $(J \times 1)$ vector of characteristics, x_g, the $\theta -$ th quantile of both male and female (log) wages, w_g; is linear

$$Q_\theta(w_g | x_g) = \beta'_{g\theta} x_g;$$

giving rise to the linear quantile regression model

$$w_g = \beta'_{g\theta} x_g + u_{g\theta}; \quad (2)$$

[4] Subscript O refers to Oaxaca.

where $Q_\theta(u_{g\theta} \mid x_g) = 0$. In this linear quantile regression the $j-$th element of $\beta_{g\theta}$ measures the return to the $j-$th characteristic on the $\theta-$th conditional quantile of the distribution of (log) wages.

Taking the expected value of the quantile regression equation (2) conditional on the (log) wage being equal to its $\theta-$th unconditional quantile, $w_g = Q_\theta(w_g)$,

$$Q_\theta(w_g) = \beta'_{g\theta} E(x_g \mid w_g = Q_\theta(w_g)) + E(u_{g\theta} \mid w_g = Q_\theta(w_g)). \qquad (3)$$

This equation expresses the $\theta-$th unconditional quantile of (log) wage as the vector of quantile regression parameters times the expected value of the vector of characteristics conditional on the unconditional quantile wage plus the expected value of the quantile regression disturbance conditional on the unconditional quantile wage. Figure (1) illustrates the meaning of equation (3). Using actual data on wages and tenure we have estimated the unconditional wage quantiles, $Q_{0.25}(w)$, $Q_{0.50}(w)$ and $Q_{0.75}(w)$ represented in Figure (1) as horizontal lines. Figure (1) also exhibits conditional quantile regression lines $Q_\theta(w \mid x)$ for $\theta = 0.25$, 0.50 and 0.75, represented as slightly upward sloping lines. Finally, the conditional expectation of tenure on wages is drawn as the line with highest slope. As equation (3) indicates, the decomposition is not exact, as the conditional expectation of tenure on wages does not cross the unconditional quantile lines at the points where these intersect the conditional quantile lines. Nevertheless, the error seems to be small.

Expression (3) allows us to write the difference between male and female $\theta-$th unconditional quantile wages as

$$Q_\theta(w_m) - Q_\theta(w_f) = A_Q + B_Q + C_Q, \qquad (4)$$

$$A_Q = (\beta'_{m\theta} - \beta'_{f\theta}) E(x_f \mid w_f = Q_\theta(w_f)),$$

$$B_Q = \beta'_{m\theta}(E(x_m \mid w_m = Q_\theta(w_m)) - E(x_f \mid w_f = Q_\theta(w_f))),$$

$$C_Q = E(u_{m\theta} \mid w_m = Q_\theta(w_m)) - E(u_{f\theta} \mid w_f = Q_\theta(w_f)).$$

Equation (4) expresses the quantile gender wage gap as the sum of three terms. The first term, A_Q, measures the difference in returns to characteristics, usually considered as discrimination. The second term, B_Q, measures the differences in characteristics. The third term, C_Q, measures unexplained differences. This third term, not present in Oaxaca's decomposition, appears here because the conditional mean of the quantile regression's disturbance term need not be equal to zero. As a result of this, the interpretation of this decomposition differs from the interpretation of the original Oaxaca's decomposition. Part of the gender wage gap at any given quantile is not explained by the quantile regressions.

An interpretation of this unexplained part follows. From the sign of the gender difference of the conditional expectation of disturbances one can immediately tell whether the estimated quantile regressions overpredict or underpredict gender (log) wage differences at a given quantile. When the difference between the conditional expected value of disturbances is positive (negative), $C_Q > 0$ ($C_Q < 0$); quantile regressions underpredict (overpredict) the unconditional quantile gender wage gap.

We consider discriminatory paying different returns for the same characteristics. In order to measure discrimination we use the gender difference in the vector of estimated coefficients times the conditional expectation of the female characteristics, term A_Q in equation (4). This is usually considered as the part of the explained gender wage gap due to discrimination. The residual part, C_Q, is the unexplained part of the wage gap, which may or may not be due to discrimination. This term, may be due entirely to discrimination, might measure no discrimination at all or anywhere in between. In the first case, $A_Q + C_Q$ measures discrimination, while, in the second case, A_Q represents discrimination. In this paper we propose an interval measure of discrimination. The end points of the interval are bounds on discrimination. The interval is $[D_Q^-, D_Q^+]$, where

$$\begin{aligned} D_Q^- &= \min\{\exp(A_Q), \exp(A_Q + C_Q)\} - 1, \\ D_Q^+ &= \max\{\exp(A_Q), \exp(A_Q + C_Q)\} - 1. \end{aligned}$$

The lower (upper) bound on discrimination is the minimum (maximum) of two quantities, since C_Q might be positive of negative.[5]

The interval measure of discrimination just introduced is a measure of absolute discrimination. As we argued in the previous section, the end points of the interval are the same regardless of the value of the term B_Q. Therefore, it is also interesting to measure discrimination relative to the unconditional gender wage differential. We propose an interval measure of relative discrimination

$$[G_Q^-, G_Q^+] = [\min\{R_0, R_1\}, \max\{R_0, R_1\}],$$

[5] There exists the possibility that A_Q could be negative. This would represent that males were discriminated, something that does not happen with our sample, nor with any other sample that we know.

where the values of R_0 and R_1 are given by

$$R_0 = \frac{A_Q}{A_Q + B_Q + C_Q} \quad \text{and} \quad R_1 = \frac{A_Q + C_Q}{A_Q + B_Q + C_Q}.$$

Let us now consider a sample counterpart of the gender quantile wage difference decomposition. This requires three pieces of information.

1. First, the $\theta-$th unconditional quantiles of (log) wages are easily estimated using the $[\theta N_g]-$th order statistic,

   $$\widehat{Q}_\theta(w_g) = w_{g\langle[\theta N_g]\rangle},$$

   where $w_{g\langle k\rangle}$ is the $k-$th order statistic of w_g, N_g is the number of individuals in the sample of gender g and $[\cdot]$ is the closest integer operator. This is a simple, yet robust to outliers, estimator of unconditional quantile wages.

2. Second, we use a Koenker and Bassett (1978) estimator of the quantile regression parameters and residuals, $\widehat{\beta}_{g\theta}$ and $\widehat{\varepsilon}_{g\theta}$ respectively.[6]

3. Third, the estimation of the conditional expectation of the vector of characteristics is covered in two parts as the components of the vector of characteristics will typically contain many binary variables and some continuous variables.

   (a) Let x_{gj}, the $j-$th element of x_g, be a binary variable. In this case we proceed by estimating a binary response model

   $$E(x_{gj} \mid w_g) = P(x_{gj} = 1 \mid w_g) = F(\alpha_j + \delta_j w_g)$$

   where $F(\cdot)$ is a distribution function, α_j and δ_j are scalar parameters and the only explanatory variables are a constant term and (log) wages. In this paper we used a Probit specification. Let $\Phi(\cdot)$ be the distribution function of the standardized normal distribution and $\widehat{\alpha}_j$ and $\widehat{\delta}_j$ be the Probit estimates. The required conditional expectation is estimated as

   $$\widehat{E}(x_{gj} \mid w_g = Q_\theta(w_g)) = \Phi(\widehat{\alpha}_j + \widehat{\delta}_j \widehat{Q}_\theta(w_g)).$$

[6] See Appendix A for a description of the estimator of the quantile regression model.

(b) Let x_{gk}, the $k-$th element of x_g, be a continuous variable. In this case we proceed by estimating a linear mean regression model

$$E(x_{gk} \mid w_g) = \alpha_k + \delta_k w_g$$

where α_j and δ_j are scalar parameters and the only explanatory variables are a constant term and (log) wages. Let $\widehat{\alpha}_k$ and $\widehat{\delta}_k$ be the OLS estimates. The required conditional expectation is estimated as

$$\widehat{E}(x_{gk} \mid w_g = Q_\theta(w_g)) = \widehat{\alpha}_k + \widehat{\delta}_k \widehat{Q}_\theta(w_g).$$

5 Other measures of discrimination at quantiles.

There is at least one previous attempt to measure gender wage discrimination at quantiles. García, Hernández and López (1988) used a measure of discrimination based on a decomposition of gender wage differences at conditional quantiles. They consider the gender wage gap at a given quantile conditional on the vector of explanatory variables evaluated at the unconditional mean. The decomposition of interest in this case is

$$Q_\theta(y_m \mid x_m = E(x_m)) - Q_\theta(y_f \mid x_f = E(x_f)) = \beta'_{\theta m} E(x_m) - \beta'_{\theta f} E(x_f),$$

$$= \left(\beta'_{\theta m} - \beta'_{\theta f}\right) E(x_f) + \beta'_{\theta m}(E(x_m) - E(x_f)). \quad (5)$$

Even though, the decomposition of conditional quantiles involves no unexplained part, it is more reasonable to compare gender wage difference at unconditional quantiles. There are two reasons why we think it is not appropriate to measure discrimination at conditional quantiles.

First, the GHL decomposition leads to the following gender wage gap decomposition

$$E(y_m) - E(y_f) = A_{GHL} + B_{GHL} + C_{GHL},$$

$$A_{GHL} = \left(\beta'_{\theta m} - \beta'_{\theta f}\right) E(x_f),$$

$$B_{GHL} = \beta'_{\theta m}(E(x_m) - E(x_f)),$$

$$C_{GHL} = E(u_{m\theta} \mid x_m = E(x_m)) - E(u_{f\theta} \mid x_f = E(x_f)).$$

Therefore, the GHL decomposition (5) is in fact a decomposition of the mean gender wage gap where the residual part, C_{GHL}, is not taken into account.

Second, the GHL decomposition evaluates the vectors of characteristics of men and women at the same points, the vectors of mean values, regardless of which quantile is considered. This might be inappropriate, as the following example illustrates. Returns to primary education increase from low to high quantiles, both for men and women. However, most of the people with only primary education has wages in the lower part of the distribution of wages. Now, suppose we want to measure discrimination at the 10^{th} quantile, where there is a high proportion of people with primary studies, and at the 90^{th} quantile, where there is a low proportion of people with only primary studies. The GHL measure of discrimination would weight the contribution of primary studies to discrimination using the mean of the variable, that is, the proportion of people with only primary studies in the entire sample, both at the 10^{th} and 90^{th} quantiles. However, one might consider more appropriate to weight male-female differential in returns to primary education at a given quantile according to the proportion of people with only primary studies at that quantile. That is precisely what the measure proposed in this paper does.

6 The empirical results.

The data comes from the Spanish sample of the Survey of Wage Structure carried out in the European Union in October of 1995. In the Spanish case, the survey was conducted by the Instituto Nacional de Estadística (INE) at the establishment level. This survey covers firms with ten or more workers of all sectors and provinces. The survey contains information on employed individuals in firms with ten or more employees. To give an idea of how representative the sample is, the population of workers at firms with ten or more workers represented 70.75% (72.95% men and 66.74% women) of the total population of workers in Spain in October of 1995.[7]

6.1 The gender wage gap.

The usual procedure to measure the male-female wage differential is to consider the difference between the average male wage and its female counterpart. In our sample, the average male hourly wage was $\overline{W}_m = 1255.02$

[7] See appendix B for a detailed description of the data set.

Spanish pesetas, whereas the female hourly wage was $\overline{W}_f$ = 947:80: Therefore, the male-female average wage di¤erential was $\overline{W}_m$ ¡ $\overline{W}_f$ = 307:22 pesetas.[8] When we do the same calculations but consider log hourly wages the male-female average wage gap di¤erential turns out to be $\overline{w}_m$ ¡ $\overline{w}_f$ = 6:9815 ¡ 6:7266 = 0:2549; where $w_g = \ln W_g$. This gap can be due, at least partially, to di¤erences in productivity between the population of males and females in our sample.

Figure (2) shows nonparametric estimates of the density functions of male and female (log) hourly wages.[9] The male wage density is displaced rightward with respect to the female wage distribution, indicating a not negligeable gender wage gap. The gender gap is better viewed in Figure (3) which exhibits the empirical cumulative density function of male and female (log) hourly wages. The horizontal distance between the two functions is the gender gap at that quantile. Figure (4) plots the gender wage gap as a function of the quantile index. The gender gap is decreasing within the …rst decile, then increases until the median, then decreases up until the 75 percentile, and from then on the gap is increasing. The gender wage gap is far from being constant within the wage distribution. This changing gender wage gap suggests that discrimination will also change when measured at di¤erent quantiles.

6.2 Returns to characteristics.

Next we compute linear and quantile regressions. Following the usual practice in the …eld, the factors controlled for in wage equations are: education, experience (proxied by age) and tenure. To consider the demand side of the labor market, sector and regional dummies are also included in the wage equations. We also control for …rm size, the type of labor agreement that settles wages in the …rm, if the …rm is a public or private one, and the occupation and type of contract the individual has. Except age and tenure, the other explanatory variables are categorical.[10]

We estimate separate wage equations for men and women. The conditional mean equation was estimated by OLS. The conditional quantile equations were estimated by quantile regression at quantiles µ = 0:10; 0:25; 0:50; 0:75; 0:90g: Results are shown in Table 1a for men and 1b for women. Look-

[8] Using the Spanish peseta US dollar exchange rate, at the time when the survey was carried out, the mean male hourly wage was 6.96 US dollars, the mean female wage was 5.25 US dollars and the wage gap was equal to 1.70 US dollars.

[9] Densities were estimated using an adaptive Epanechnikov kernel.

[10] The presence of dummy variables may posse a problem when comparing returns to a particular explanatory variable for men and women. This problem is typically ignored in studies of gender wage discrimination. See appendix C for details on this.

ing at the quantitative results of tables 1a and 1b, we observe that all the variables are signi…cant at 5% level and the estimated coe¢ cients take the expected signs. We next describe the results in more detail.

Returns to age are positive and higher at top quantiles, both for men and women. At low quantiles returns to age are higher for women, but at the median and higher quantiles, returns to age are higher for men.

Returns to education increase with the level of education, on the mean and quantile regressions, both for men and women. For men, the return to secondary or higher education increases as one moves from the lowest to the highest quantile (except at the 25^{th} quantile for secondary education). However, the return to primary education for men decreases as the quantile increases (again, except at the 25^{th} quantile). Returns to secondary or higher education for women exhibit a decline at the 25^{th} and 50^{th} quantiles increasing afterwards. For women, returns to 3-year college are equal to those to secondary education from the 10^{th} to the 75^{th} quantile, while are lower at the 90^{th} quantile, a striking di¤erence with respect to men. Comparing the results of the quantile regressions with those of the mean regression we …nd higher returns to 5-year college education for women than for men at the 10^{th} and 90^{th} quantiles, and lower returns for women than for men at the other quantiles, while we …nd a similar return to 5-year college education at the mean for men and women.

Years of tenure in the …rm increase worker's wage. One additional year of tenure increases women's wages more than men's, on average. The return to an additional year of tenure is also higher for women than for men at all quantiles. We also observe that the return to tenure decreases steadily across the higher quantiles. Furthermore, we …nd that this decrease is more pronounced for men than for women.

As expected, we observe that the wage increases with the rank of the occupation for both men and women. On average, male workers earn relatively more than women as executives and quali…ed workers in the industry sector than as non-quali…ed workers. The contrary is observed for the rest of the occupations (liberal profession, technician, clerical and quali…ed in the service sector). Looking at the quantile regressions results, we also observe that males earn more than women as executives and quali…ed workers in the industry sector at all quantiles. In addition, we …nd that men earn more than women also as quali…ed workers, clerical and technicians at the 75^{th} and 90^{th} quantiles.

Our results show that male and female workers who have an inde…nite labor contract earn higher wages than those who have a …xed-term contract. The di¤erence in wages between the two types of labor contract is much wider for the upper quantiles. If we look now at gender di¤erences between the estimated coefficients at a given quantile, we find that the gender differential in returns increases with quantiles.

Working in the public sector increases wages for men and specially women. For women, the public sector premium is much higher at the lower quantiles. The gender differential in returns widens at higher quantiles.

Our results show that larger firms pay higher wages for both men and women. The relative benefits from working for large firms are greater for men than for women. The male-female estimated coefficients differentials decreases from the 10^{th} quantile to the 90^{th} quantile.

We find that low-level (firm and establishment) collective bargaining gets higher wages than high-level collective bargaining, as expected, for both men and women, and the returns are higher for men than for women. We find this result on the mean regression as well as at the different quantile regressions. We also find that the male-female gap of the estimated coefficients follows an U-form pattern as we go from the 10^{th} to the 90^{th} quantile.

Relative to low GDP regions, workers living in medium and high GDP regions earn more both on average and at different quantiles. We observe that this premium is greater for women than for men.

6.3 Discrimination.

Table 2 shows the decomposition of the observed male-female wage gap both for the mean and the quantile estimations. The rows present the decomposition of the observed gender wage gap at different points of the wage distribution (10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} quantiles and the mean). The first column of results presents the observed wage gap at selected quantiles, $\hat{Q}_\theta(w_m) - \hat{Q}_\theta(w_f)$; and the observed wage gap at the unconditional mean $\overline{w}_m - \overline{w}_f$. The second, third and forth columns present the part of the estimated wage gap due to differences in returns to the explanatory variables, $\hat{A}_Q$, the part due to differences in endowments of the explanatory variables, $\hat{B}_Q$; and differences in residuals or unexplained part, $\hat{C}_Q$, respectively. Figure (5) represents the decomposition at different quantiles. Differences in characteristics and returns to characteristic increase with the quantile index. The unexplained part does not exhibit a clear pattern, it is positive at the median, where it reaches its maximum value, and negative at all other quantiles.

Table 3 presents the measures of discrimination. The first finding regards the magnitude of discrimination relatively to the total wage gap. Let us start our analysis with the standard decomposition based on the mean regression. Our results show that 75% of the average gender wage gap is explained by differences in returns and 25% is explained by differences in observed characteristics. This decomposition leads to a estimated discrimination coefficient of $\hat{\delta}_O = 0.21$. This figure tells us that the observed male-female average wage ratio is 21% higher than the one that would prevail in a non-discriminatory labor market. In other words, if men and women had the same value of the explanatory variables then men would earn, on average 21% more than women.

This finding is in sharp contrast with some previous empirical evidence. Ugidos (1997) finds that, using the Spanish survey Encuesta sobre Discriminación Salarial (EDS) of 1988, 63% of the gender wage gap at the mean is due to differences in characteristics and only 37% is due to differences in returns to those characteristics. Manero (1999), using the Spanish SWS, the same survey that we use in this paper, but restricting the analysis to individuals who hold a university degree and are 45 or less, finds that 61% of the gender wage difference is due to differences in returns. However, our findings are very similar to those of García, Hernández and López (1998) who using the Spanish survey Encuesta de Conciencia, Biografía y Estructura de Clase (ECBC) of 1991 find that 74% of the gender wage gap is due to differences in returns. They obtain almost the same figure using a different survey.

We move now to study the results at quantiles. Our results show that the estimated discrimination coefficients $[\hat{\delta}^-_Q; \hat{\delta}^+_Q]$ increase with quantiles. The estimated lower bound of discrimination increases about 30%, whereas the upper bound increases about 35%.

The last two columns of Table 3 report the end points of the interval $[\hat{\theta}^-_Q; \hat{\theta}^+_Q]$, lower and upper bounds on the measure of relative discrimination. The results reveal that discrimination relative to total gender wage gap decreases as we move to higher quantiles. Therefore, relative to the total gender wage gap the highest discrimination is at the lowest quantile.

Figure (6) shows the measures of absolute and relative discrimination at different quantiles. While absolute discrimination increases with quantiles, relative discrimination decreases from the 10^{th} centile up until the median, then increases at the 75^{th} centile and decreases again at the 90^{th} centile.

The finding of a decreasing measure of relative discrimination contrasts with GHL who find that both absolute and relative discrimination increase as one moves from low to high quantiles. This apparent contradiction between the two pieces of evidence could be due to the fact that we use a different sample or, perhaps, to the fact that we use a different measure of discrimination. To determine which of these two differences is responsible for the differences in results, we computed the measure of discrimination used by GHL with our data. The result, not reported here, is that the degree of discrimination increases, as we move from the lowest quantile to the highest, both in absolute and relative terms, as GHL find. Hence, the choice of discrimination measure determines the result. As argued above, there are two reasons to prefer our measure of discrimination. First, GHL measure is not based in a decomposition of the observed gender wage differential. Second, their measure weights returns differentials equally at all quantiles, regardless of the density of population at any particular quantile. Hence we conclude that, discrimination seems to be a lower fraction of the gender wage gap of high earners than of low earners.

6.4 Contribution to the pay gap.

Once the total extent of discrimination has been analyzed, we turn to study the contribution of different factors. Figures (7), (8) and (9) show the contribution of each variable to differences in returns to characteristics and differences in endowments, as well as the error term of the decomposition at the 10^{th} quantile, mean and 90^{th} quantile respectively.

The greater contribution to discrimination corresponds to the constant term. This reflects a very high degree of discrimination unrelated to the explanatory variables. Age has a negative contribution to discrimination at the 10^{th} quantile and a positive contribution at higher quantiles. Tenure has a negative contribution to discrimination at the 10^{th} and 90^{th} quantiles as well as the mean. At the 10^{th} quantile and the mean, to be a qualified worked in the industry sector contributes to discrimination, whereas that contribution disappears at the 90^{th} quantile. Working in the private sector is another important source of discrimination, more in the 10^{th} quantile than in the mean or the 90^{th} quantile. Differences in returns to education seem to have a very little contribution to discrimination. There seems to be more discrimination in larger firms at the 10^{th} quantile and the mean, but not at the 90^{th} quantile.

7 Conclusions

In this paper we have developed a new method of measuring gender wage discrimination at different quantiles of the distribution of wages. The method mimics the steps followed in the construction of Oaxaca's measure. The measures of discrimination proposed are based on a decomposition of the gender difference of unconditional quantile wages as the sum of three terms: (i) the difference in returns to the same characteristics, (ii) the difference in characteristics and (iii) an unexplained part.

Using the Spanish sample of the SWS we reach two main conclusions. First, there are quantitatively important differences in returns at different locations of the distribution of wages. Second, in absolute terms discrimination increases as we move upward in the distribution of wages, whereas discrimination relative to total quantile gender wage differentials experiments a decrease when we consider higher quantiles.

A Quantile Regression

The quantile regression model assumes that conditional on a vector of characteristics, x, the $\theta-$th quantile of y is linear

$$Q_{\theta}(y_i \mid x_i) = \beta_{\theta}' x_i; \tag{6}$$

giving rise to the linear quantile regression model

$$y_i = \beta_{\theta}' x_i + u_{\theta i}; \tag{7}$$

where $Q_{\theta}(u_{\theta} \mid x) = 0$: The Koenker and Bassett (1978) estimator of the quantile regression model solves

$$\min_{\theta} \sum_{i=1} \rho(u_{\theta i})$$

where $\rho(a) = (\theta 1(a \geq 0) + (1 - \theta) 1(a < 0)) |a|$: This problem can be shown to have a linear programing representation. Under some regularity conditions, The Koenker and Bassett (1978) estimator has a normal asymptotic distribution. In this paper we use de Design Matrix Bootstrap (DMB) method to estimate the covariance matrix of the vector of parameter estimates.[11]

B The data.

The SWE contains very detailed information about each worker's wage, individual and job characteristics. The data from this survey is provided by the INE following an anonymity process. The researcher should specify the level of disaggregation of six variables: region, sector, firm size, type of labor agreement, product market and state ownership. If in any cell there are less than five observations, the INE does not provide those data in order to preserve anonymity. Thus, if the researcher wants a very fine description of

[11] See Buchinsky (1994) for details.

some of these explanatory variables, many cells will have very few observations and the sample will be heavily truncated. In order to avoid a heavy truncation of the sample, we have chosen to use a small number of categories for each of those six variables. In particular, we aggregated the seventeen Spanish regions into three categories, low, medium and high GDP.[12] We aggregated all nine sectors available into two: services and industry, the latter includes construction. We aggregated the …ve …rm-size groups into three categories of 10 to 19, 20-99 and 100 or more employees. Out of the …ve types of collective agreement available we gather them into two, at the …rm or establishment level and at sectorial, provincial or national level. We did not consider the "product market" variable in our request. Finally, we collected the four types of "state ownership" into two, private and others, the latter including public, mostly public and others. In addition to this, we aggregated the 68 education groups into …ve groups.[13] We also aggregated the two-digit occupations of the CNO-94 into seven groups.[14] The sample size is 177,114. We removed from the sample all those observations corresponding to: trainees (1,170), those who did not work the entire month of October (5,192), those who worked part time (6,306), those who did not report the wage (25) and those whose reported wage was less than 100 pts/hour (151). The …nal sample size is 164,270, 129,061 men and 35,209 women.

Table B1 shows the mean and quantiles of wages, age and teneaure. The average male wage per hour is 1255 Pesetas whereas the average female wage per hour is almost 948 Pta. The average female wage is 75.5% of the average wage of men. Women have, on average, about two and a half years of tenure less than men. Gender tenure di¤erences increases from one year at the 10^{th} quantile to three years at the 90^{th}quantile. The female to male wage ratio varies along the wage distributions (10 percentage points between the lowest to the highest quantile). We observe that at the 10^{th} percentile females wage rate is 84% that of males. The ratio decreases until we reach the median, 75.1%, then increases a slightly to 76.5% at the 75^{th}quantile and goes down again reaching the lowest level at the 90^{th}quantile, 74.5%. This simple ratio shows us important di¤erences in the gender wage gap along

[12] Low GDP regions include Andalucía, Cantabria, Castilla La Mancha, Castilla León, Extremadura, Galicia and Murcia. Medium GDP regions include Aragón, Asturias, Canarias, Comunidad Valenciana and La Rioja. High GDP regions include Baleares, Cataluña, Madrid, Navarra and País Vasco.

[13] Less than primary studies, primary studies, secondary studies (including high school and three-year vocational studies), three-year college (also including …ve-year vocational studies) and …ve-year college (including masters and Ph.D.'s).

[14] Executives, liberal pro¤esionals, technicians, clericals, quali…ed worker in the services sector, quali…ed workers in industry or construction and non-quali…ed workers.

wage distributions.

Women are younger than men on average. The gender age difference increases as we move from the lowest to the highest quantile. Women have, on average, about two and a half years of tenure less than men. Gender tenure differences increases from one year at the 10^{th} quantile to three years at the 90^{th}quantile.

Looking at Table B2 we find that women are also more educated on average than men. Our data also show important differences among men and women in occupations. More than 40% of women work as clerical and qualified workers in the service sector while 51% of men work as qualified workers in the industry and construction sectors. The fixed-term contracts are more frequently used for women (29%) than for male workers (23%). The evidence presented by Jimeno and Toharia (1993) shows that workers with indefinite contract earns 9 to 11 percent more than those with fixed-term contracts. De la Rica and Felgueroso (1999) find that this difference increases with qualification. Above 92% of women and men in the sample work in the private sector. On average, there are no marked differences in the size of firms where men and women work. Over 40% of men and women work for large firms. About 22% of women's and 29% of men's wages are settled by collective bargaining at the firm or establishment level. At last, 46% of women and 39% of men live in "high GDP" regions.

C The dummy variables.

Most of the conditioning variables are categorical. This posses a problem for discrimination analysis that is typically overlooked in the literature. To illustrate this potential problem, let us consider the following example. Suppose the only explanatory variable was education and there were J categories of studies. The equation considered is a linear or quantile regression of the form

$$w_{gi} = \alpha_g + \sum_{j=1}^{J} \beta_{gj} D^j_{gi} + u_{gi} \tag{8}$$

where α_g and β_{gj} are parameters and D^j_{gi} is a dummy variable that takes the value of one when individual i has studies in category j; and zero otherwise. This model cannot be estimated, since there is exact multicolinearity (the constant term is the sum of the J dummies). Typically, one of the dummies, say the first one, is excluded from the regression to attain identification. The regression equation is now

$$w_{gi} = \tilde{\alpha}_g + \sum_{j=2}^{J} \tilde{\beta}_{gj} D_{gi}^j + u_{gi}; \tag{9}$$

where $\tilde{\alpha}_g = \alpha_g + \beta_{g1}$ and $\tilde{\beta}_{gj} = \beta_{gj} - \beta_{g1}$. As long as the interpretation of the transformed coefficients is taken into account, this specification posses no problem for most econometric applications. However, for discrimination studies this specification may result in erroneous inference. Suppose that we estimate equation (9) for men and women and find that $\tilde{\beta}_{m2} < \tilde{\beta}_{f2}$. Can we say that the return to the education level $j = 2$ is greater for women than for men? The answer is no, for suppose that $\beta_{m2} > \beta_{f2}$ and $\beta_{m1} > \beta_{f1}$, that is, returns to levels 1 and 2 of education are greater for men than for women. However, if it is the case that $(\beta_{m1} - \beta_{f1}) > (\beta_{m2} - \beta_{f2}) > 0$; then $\tilde{\beta}_{m2} < \tilde{\beta}_{f2}$. Therefore, in evaluating the difference in returns between men and women it is very important to take into account the return of the omitted category. This can be easily done if we estimate equation (8) subject to

$$\sum_{j=1}^{J} \beta_{gj} = 0.$$

Solving for β_{g1} and substituting the result in (8)

$$w_{gi} = \alpha_g + \sum_{j=2}^{J} \beta_{gj} (D_{gi}^j - D_{gi}^1) + u_{gi}.$$

Therefore, expressing the dummies as differences with respect to the dummy of the omitted category allows us to identify the true effects of the categorical variable. In addition, the effect of the omitted category on wages is given by $\beta_{g1} = -\sum_{j=2}^{J} \beta_{gj}$. This later procedure is the one used throughout this paper.

References

[1] Abadie, A. (1997), "Changes in the Spanish labor income structure during the 1980's: a quantile regression approach," Investigaciones Económicas 21, 253-272.

[2] de la Rica, S. and F. Felgueroso (1999), "Wage di¤erentials between permanent and temporal workers: Further evidence" mimeo.

[3] Buchinsky, M. (1994), "Changes in the U.S. wage structure 1963-1987: an application of quantile regression," Econometrica, 62(2), 405-458.

[4] Buchinsky, M. (1995a), "Estimating the asymptotic covariance matrix for quantile regression models: A Monte Carlo study," Journal of Econometrics 68, 303-338.

[5] Buchinsky, M. (1995b), "Quantile regression, Box-Cox transformation model, and the U.S. wage structure, 1963-1987," Journal of Econometrics 65, 109-154.

[6] Chamberlain, G. (1994), "Quantile regression, censoring and the structure of wages," in C. A. Sims eds. Advances in econometrics 6th world congress. vol. 1. Cambridge University Press.

[7] García, J., P. J. Hernández and A. López (1998) "How wide is the gap? An investigation of gender wage di¤erences using quantile regression," working paper Universitat Pompeu Fabra, Barcelona.

[8] Jimeno, J. F. and L. Toharia (1993), "The e¤ects of …xed term employment on wages: Theory and evidence from Spain," Investigaciones Económicas, vol XVII(3) pp. 475-494.

[9] Koenker, R. and G. Bassett (1978), "Regression quantiles." Econometrica, 46, 33-50.

[10] Manero, M. (1999), "La discriminación salarial en el mercado de trabajo español." Tesina CEMFI n^{o}9906.

[11] Mincer (1974), Schooling, Experience and Earning. New York: Columbia University Press.

[12] Oaxaca, R. (1973), "Male-female wage di¤erentials in urban labor markets." International Economic Review, 14(3), 693-709.

[13] Pereira, P. T. and Martins, P. S. (2000) "Does education reduce wage inequality? quantile regressions evidence from fifteen european countries" IZA Discussion paper No. 120.

[14] Reilly, B. (1999) "The gender pay gap in Russia during the transition, 1992-96," Economics of Transition, vol 7(1), pp. 245-264.

[15] Ugidos, A. (1997) "Gender Wage Discrimination in the Spanish Labor Market." Revista Española de Economía, vol. 14(1), pp. 3-21.

[16] Willis, R. J. (1986) "Wage determinants: A Survey and Reinterpretation of Human Capital Earnings Functions". In Handbook of Labor Economics. Ashenferter, O and Layard, R (ed). Amsterdam: North-Holland.

Table 1a: Returns to Men's characteristics.

	µ = 0:10	µ = 0:25	µ = 0:50	µ = 0:75	µ = 0:90	mean
Age	0.0044	0.0049	0.0059	0.0075	0.0096	0.0068
	0.0001	0.0001	0.0001	0.0002	0.0002	0.0001
Less primary	-0.1522	-0.1567	-0.1846	-0.2039	-0.2071	-0.1847
	0.0090	0.0055	0.0036	0.0082	0.0116	0.0054
Primary	-0.0784	-0.0996	-0.1184	-0.1443	-0.1510	-0.1231
	0.0036	0.0023	0.0025	0.0037	0.0051	0.0023
Secondary	0.0088	-0.0054	-0.0114	0.0022	0.0235	0.0044
	0.0034	0.0029	0.0030	0.0040	0.0056	0.0028
3-year college	0.0555	0.0594	0.0656	0.0614	0.0581	0.0612
	0.0045	0.0042	0.0028	0.0046	0.0055	0.0028
5-year college	0.1664	0.2023	0.2488	0.2845	0.2766	0.2421
	0.0085	0.0062	0.0062	0.0057	0.0126	0.0043
Tenure	0.0093	0.0085	0.0073	0.0055	0.0039	0.0068
	0.0002	0.0002	0.0001	0.0002	0.0002	0.0002
Executive	0.3065	0.3836	0.4666	0.5329	0.5745	0.4480
	0.0093	0.0121	0.0085	0.0073	0.0092	0.0044
Liberal pro¤.	0.1870	0.2096	0.2091	0.1993	0.1944	0.1953
	0.0051	0.0053	0.0064	0.0059	0.0129	0.0044
Technician	0.0468	0.0480	0.0799	0.1170	0.1437	0.0874
	0.0060	0.0037	0.0043	0.0047	0.0065	0.0030
Clerical	-0.0812	-0.0936	-0.1044	-0.1003	-0.0793	-0.0939
	0.0042	0.0030	0.0031	0.0042	0.0054	0.0032
Qualif. services	-0.1672	-0.1946	-0.2301	-0.2487	-0.2579	-0.2149
	0.0051	0.0048	0.0045	0.0035	0.0082	0.0039
Qualif. industry	-0.0756	-0.1202	-0.1599	-0.1947	-0.2272	-0.1519
	0.0031	0.0035	0.0026	0.0030	0.0043	0.0022
Non-quali…ed	-0.2163	-0.2329	-0.2612	-0.3054	-0.3482	-0.2701
	0.0044	0.0042	0.0038	0.0048	0.0081	0.0033
Service sector	-0.0006	-0.0028	-0.0019	0.0014	0.0127	0.0054
	0.0019	0.0014	0.0012	0.0018	0.0026	0.0013
Industry sector	0.0006	0.0028	0.0019	-0.0014	-0.0127	-0.0054
	0.0019	0.0014	0.0012	0.0018	0.0026	0.0013

Table 1a: Returns to Men's characteristics (Continued).

	μ = 0:10	μ = 0:25	μ = 0:50	μ = 0:75	μ = 0:90	mean
Indef. contract	0.0543	0.0535	0.0584	0.0782	0.0995	0.0733
	0.0017	0.0020	0.0014	0.0020	0.0025	0.0015
Term contract	-0.0543	-0.0535	-0.0584	-0.0782	-0.0995	-0.0733
	0.0017	0.0020	0.0014	0.0020	0.0025	0.0015
Public sector	0.0451	0.0333	0.0335	0.0385	0.0435	0.0370
	0.0030	0.0022	0.0020	0.0024	0.0037	0.0020
Private sector	-0.0451	-0.0333	-0.0335	-0.0385	-0.0435	-0.0370
	0.0030	0.0022	0.0020	0.0024	0.0037	0.0020
Less 20 wor.	-0.0897	-0.0912	-0.0953	-0.1053	-0.1171	-0.1007
	0.0030	0.0018	0.0017	0.0017	0.0027	0.0018
20-99 workers	-0.0112	-0.0146	-0.0130	-0.0085	-0.0138	-0.0098
	0.0021	0.0016	0.0017	0.0018	0.0027	0.0015
100 more wor.	0.1009	0.1058	0.1083	0.1137	0.1309	0.1106
	0.0021	0.0016	0.0018	0.0027	0.0025	0.0016
Firm labor agr.	0.0593	0.0714	0.0801	0.0748	0.0663	0.0669
	0.0018	0.0014	0.0018	0.0020	0.0021	0.0013
Provin-nat. agr.	-0.0593	-0.0714	-0.0801	-0.0748	-0.0663	-0.0669
	0.0018	0.0014	0.0018	0.0020	0.0021	0.0013
High GDP	0.0587	0.0629	0.0648	0.0606	0.0544	0.0593
	0.0020	0.0014	0.0015	0.0015	0.0034	0.0014
Med GPP	-0.0207	-0.0141	-0.0115	-0.0050	-0.0011	-0.0136
	0.0024	0.0015	0.0017	0.0019	0.0030	0.0016
Low GDP	-0.0380	-0.0488	-0.0534	-0.0556	-0.0532	-0.0457
	0.0023	0.0015	0.0014	0.0021	0.0032	0.0014
Constant	6.3909	6.5903	6.7899	6.9949	7.1941	6.7760
	0.0066	0.0065	0.0052	0.0078	0.0106	0.0051

Table 1b: Returns to women's characteristics.

	μ = 0:10	μ = 0:25	μ = 0:50	μ = 0:75	μ = 0:90	mean
Age	0.0050	0.0050	0.0053	0.0062	0.0082	0.0060
	0.0003	0.0003	0.0003	0.0003	0.0005	0.0002
Less primary	-0.1779	-0.1518	-0.1550	-0.2035	-0.2104	-0.1928
	0.0301	0.0088	0.0103	0.0130	0.0304	0.0128
Primary	-0.0739	-0.0820	-0.0983	-0.1213	-0.1486	-0.1056
	0.0074	0.0040	0.0042	0.0066	0.0088	0.0045
Secondary	0.0349	0.0220	0.0244	0.0355	0.0521	0.0365
	0.0090	0.0037	0.0045	0.0062	0.0122	0.0049
3-year college	0.0270	0.0189	0.0240	0.0357	0.0170	0.0296
	0.0102	0.0053	0.0064	0.0061	0.0105	0.0055
5-year college	0.1899	0.1929	0.2049	0.2536	0.2900	0.2323
	0.0125	0.0104	0.0093	0.0079	0.0205	0.0075
Tenure	0.0120	0.0116	0.0114	0.0106	0.0094	0.0111
	0.0004	0.0003	0.0003	0.0005	0.0006	0.0003
Executive	0.2257	0.3167	0.4133	0.5072	0.5424	0.3979
	0.0281	0.0259	0.0259	0.0307	0.0486	0.0135
Liberal pro¤.	0.1899	0.2435	0.2776	0.2556	0.2602	0.2448
	0.0162	0.0157	0.0135	0.0146	0.0174	0.0088
Technician	0.0813	0.0813	0.0957	0.1243	0.1405	0.1046
	0.0081	0.0082	0.0084	0.0090	0.0152	0.0057
Clerical	-0.0492	-0.0634	-0.0825	-0.0991	-0.0910	-0.0730
	0.0068	0.0050	0.0067	0.0080	0.0114	0.0043
Qualif. services	-0.1137	-0.1708	-0.2233	-0.2513	-0.2409	-0.1932
	0.0087	0.0060	0.0099	0.0069	0.0150	0.0054
Qualif. industry	-0.1428	-0.1903	-0.2223	-0.2418	-0.2846	-0.2117
	0.0083	0.0057	0.0070	0.0075	0.0142	0.0051
Non-quali…ed	-0.1912	-0.2168	-0.2585	-0.2948	-0.3266	-0.2695
	0.0119	0.0063	0.0082	0.0068	0.0137	0.0058
Service sector	0.0097	0.0081	0.0139	0.0220	0.0368	0.0203
	0.0035	0.0023	0.0025	0.0026	0.0037	0.0022
Industry sector	-0.0097	-0.0081	-0.0139	-0.0220	-0.0368	-0.0203
	0.0035	0.0023	0.0025	0.0026	0.0037	0.0022

Table 1b: Returns to women's characteristics. (Continued)

	μ = 0:10	μ = 0:25	μ = 0:50	μ = 0:75	μ = 0:90	mean
Inde.... contra.	0.0448	0.0379	0.0410	0.0494	0.0778	0.0584
	0.0036	0.0020	0.0025	0.0034	0.0043	0.0025
Term contra.	-0.0448	-0.0379	-0.0410	-0.0494	-0.0778	-0.0584
	0.0036	0.0020	0.0025	0.0034	0.0043	0.0025
Public sector	0.0869	0.0729	0.0634	0.0489	0.0470	0.0597
	0.0054	0.0040	0.0053	0.0045	0.0045	0.0037
Private sector	-0.0869	-0.0729	-0.0634	-0.0489	-0.0470	-0.0597
	0.0054	0.0040	0.0053	0.0045	0.0045	0.0037
Less 20 wor.	-0.0549	-0.0580	-0.0681	-0.0919	-0.0992	-0.0761
	0.0057	0.0044	0.0035	0.0035	0.0054	0.0033
20-99 wor.	-0.0044	-0.0101	-0.0094	-0.0071	-0.0223	-0.0104
	0.0042	0.0031	0.0033	0.0021	0.0053	0.0026
100 more wor.	0.0593	0.0682	0.0775	0.0990	0.1215	0.0864
	0.0048	0.0038	0.0026	0.0035	0.0061	0.0027
Firm labor agr.	0.0404	0.0530	0.0698	0.0640	0.0390	0.0542
	0.0023	0.0028	0.0034	0.0037	0.0048	0.0024
Provi.-nat. agr.	-0.0404	-0.0530	-0.0698	-0.0640	-0.0390	-0.0542
	0.0023	0.0028	0.0034	0.0037	0.0048	0.0024
High GDP	0.0551	0.0599	0.0618	0.0616	0.0580	0.0582
	0.0031	0.0021	0.0030	0.0046	0.0047	0.0025
Med GPP	0.0071	0.0029	0.0026	0.0043	0.0044	0.0015
	0.0031	0.0022	0.0029	0.0036	0.0054	0.0029
Low GDP	-0.0621	-0.0629	-0.0645	-0.0659	-0.0624	-0.0598
	0.0042	0.0016	0.0027	0.0038	0.0042	0.0027
Constant	6.2164	6.4175	6.6228	6.8002	6.9679	6.5899
	0.0107	0.0117	0.0120	0.0147	0.0210	0.0096

Table 2: Gender wage gap decomposition.

Quantiles	$\hat{Q}_\theta(w_m) - \hat{Q}_\theta(w_f)$	$\hat{A}_Q$	$\hat{B}_Q$	$\hat{C}_Q$
$\theta = 0.10$	0.1740	0.1689	0.0279	-0.0227
$\theta = 0.25$	0.2082	0.1775	0.0365	-0.0059
$\theta = 0.50$	0.2861	0.1867	0.0711	0.0283
$\theta = 0.75$	0.2681	0.2188	0.0650	-0.0157
$\theta = 0.90$	0.2944	0.2236	0.0915	-0.0207
	$\overline{w}_m - \overline{w}_f$	$\hat{A}_O$	$\hat{B}_O$	
Mean	0.2548	0.1914	0.0635	

Table 3: Gender wage discrimination.

Quantiles	D_Q^-	D_Q^+	G_Q^-	G_Q^+
$\theta = 0.10$	0.1574	0.1840	0.8398	0.9705
$\theta = 0.25$	0.1872	0.1943	0.8244	0.8529
$\theta = 0.50$	0.2052	0.2398	0.6525	0.7513
$\theta = 0.75$	0.2252	0.2445	0.7575	0.8159
$\theta = 0.90$	0.2249	0.2506	0.6892	0.7596
	$\hat{D}_O$		$\hat{G}_O$	
Mean	0.2109		0.7509	

Table B1: Wages, Age and Tenure of Men and Women.

	Quantiles					Mean
Variables	μ = 10	μ = 25	μ = 50	μ = 75	μ = 90	
			Men			
Hourly wage	595.82	732.82	1018.29	1474.09	2161.28	1255.02
(Log) wage	6.3899	6.5971	6.9259	7.2958	7.6784	6.9815
Age	26	31	39	48	55	39.953
Tenure	1	2	8	20	26	11.609
			Women			
Hourly wage	500.65	595.21	764.93	1127.41	1610.15	947.80
(Log) Wage	6.2159	6.3889	6.6398	7.0277	7.3841	6.7266
Age	24	27	34	41	49	34.981
Tenure	0	2	6	17	23	9.189

Table B2: Qualitative variables.

Variables	Men	Women
Less than primary	0.026	0.014
Primary	0.626	0.564
Secondary	0.154	0.218
3-year college	0.135	0.135
5-year college	0.059	0.069
Executive	0.049	0.014
Liberal pro¤esion	0.055	0.044
Technician	0.111	0.105
Clerical	0.093	0.277
Quali…ed (services)	0.068	0.163
Quali…ed (industry)	0.513	0.266
Non-quali…ed	0.111	0.131
Services	0.308	0.457
Industry and const.	0.692	0.543
Fixed-time contract	0.231	0.286
Inde…nite contract	0.769	0.714
Public sector	0.077	0.073
Private sector	0.923	0.927
Less than 20 workers	0.188	0.167
20-99	0.396	0.379
100 or more	0.416	0.454
Firm level labor agree.	0.289	0.782
Provincial or national	0.711	0.218
High GDP province	0.388	0.464
Medium	0.252	0.230
Low	0.360	0.306

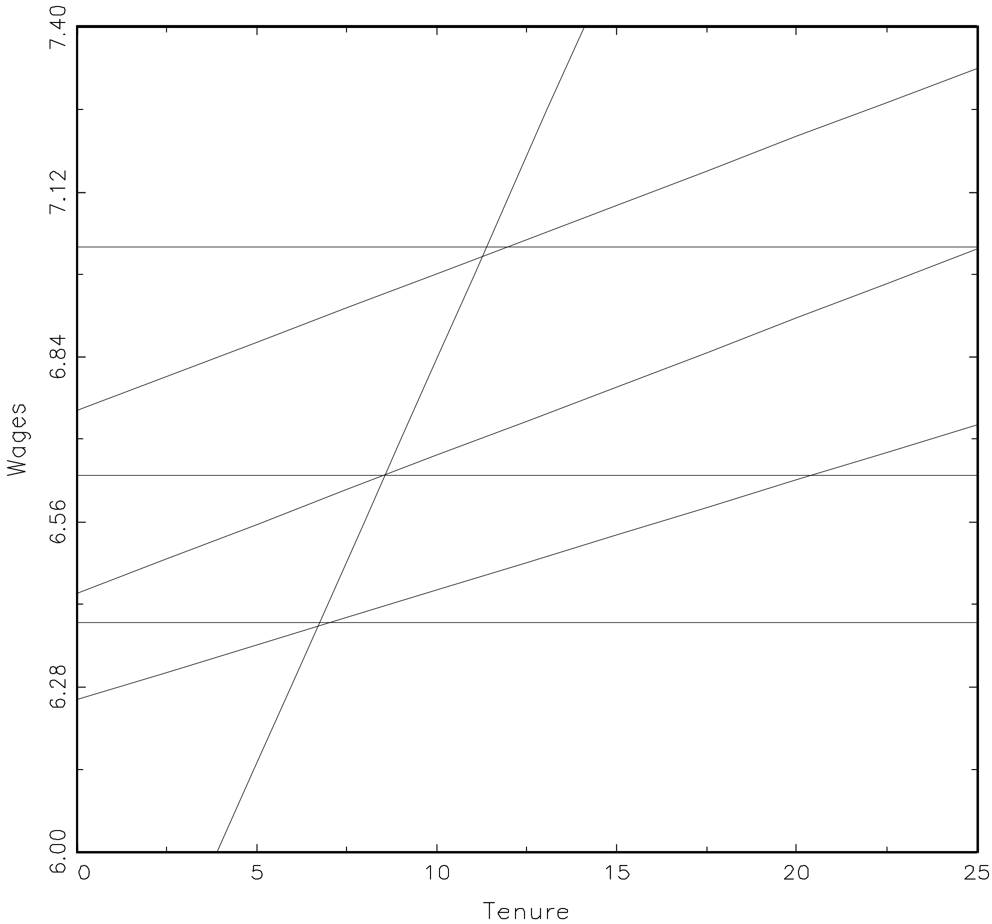

Figure 1: Conditional and unconditinal quantiles.

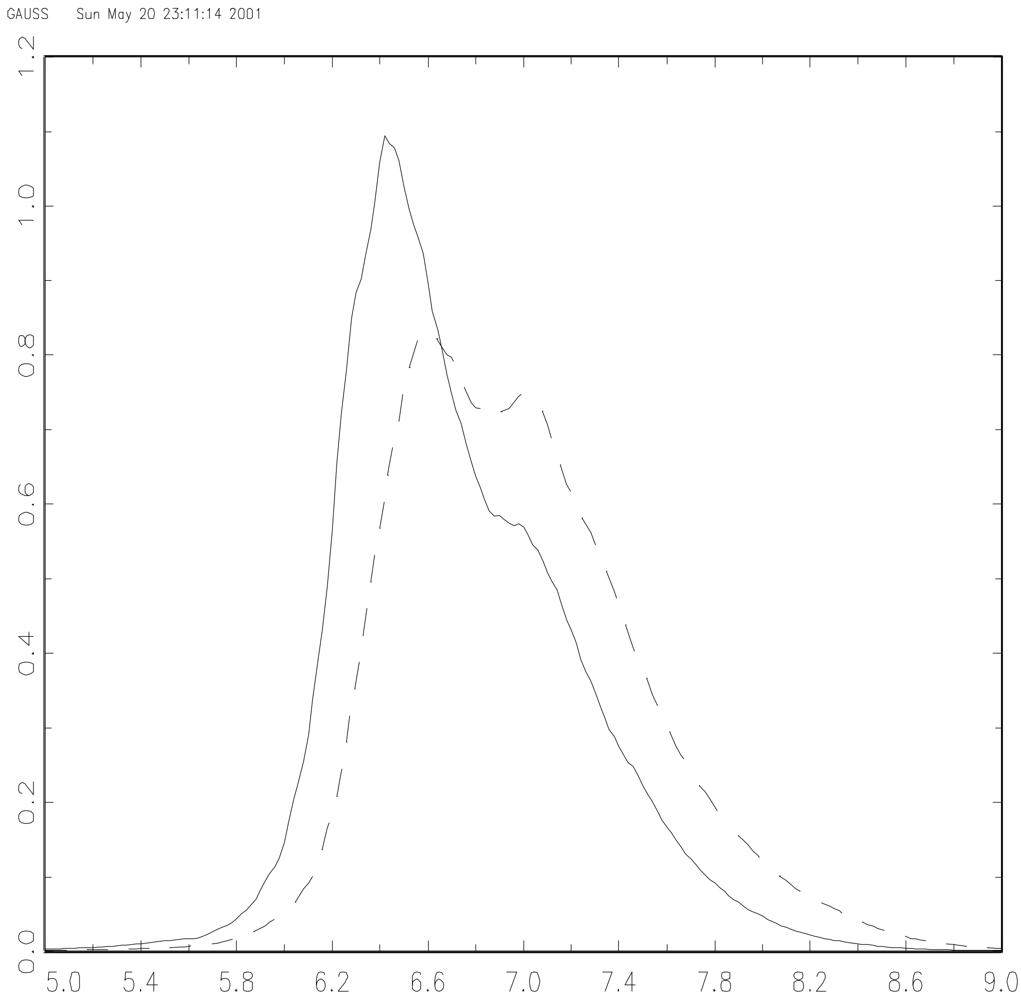

Figure 2: Male (solid) and Female (broken) wage densities.

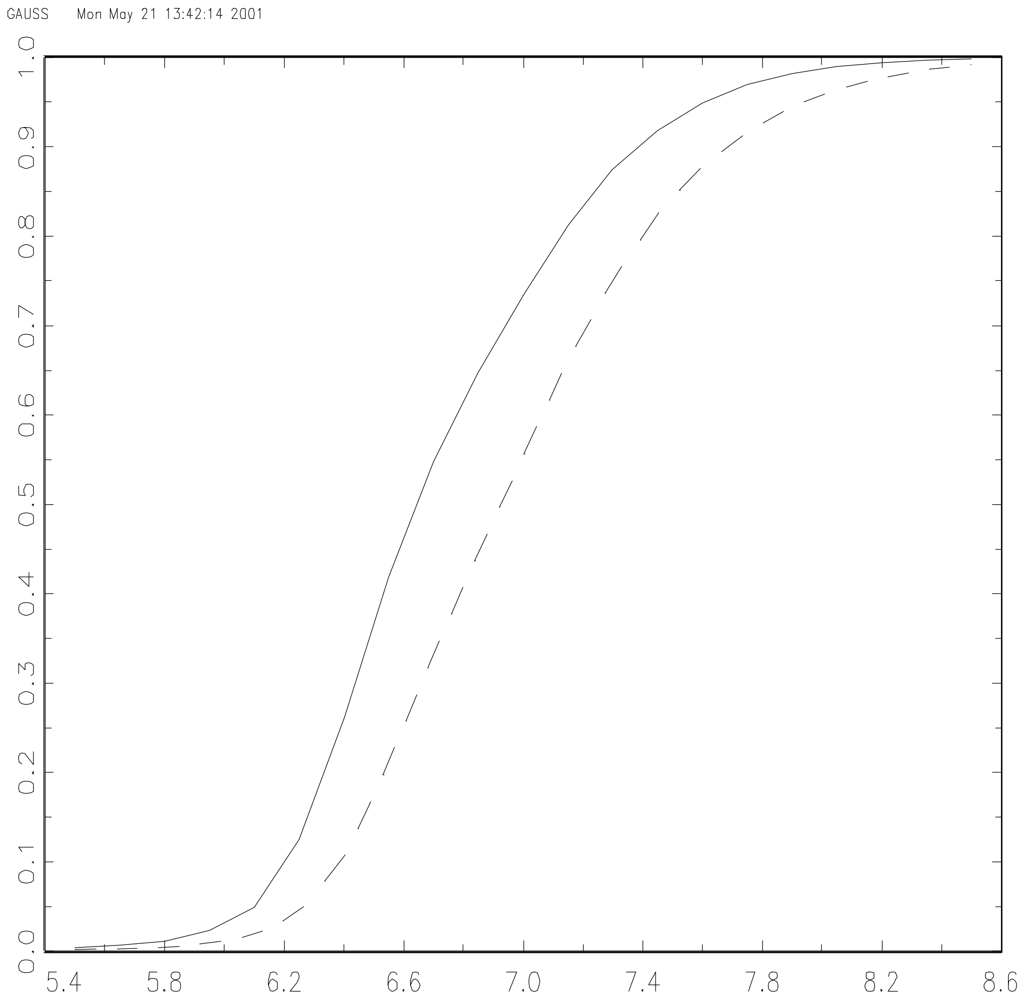

Figure 3: Male (solid) and female (broken) wage distribution functions.

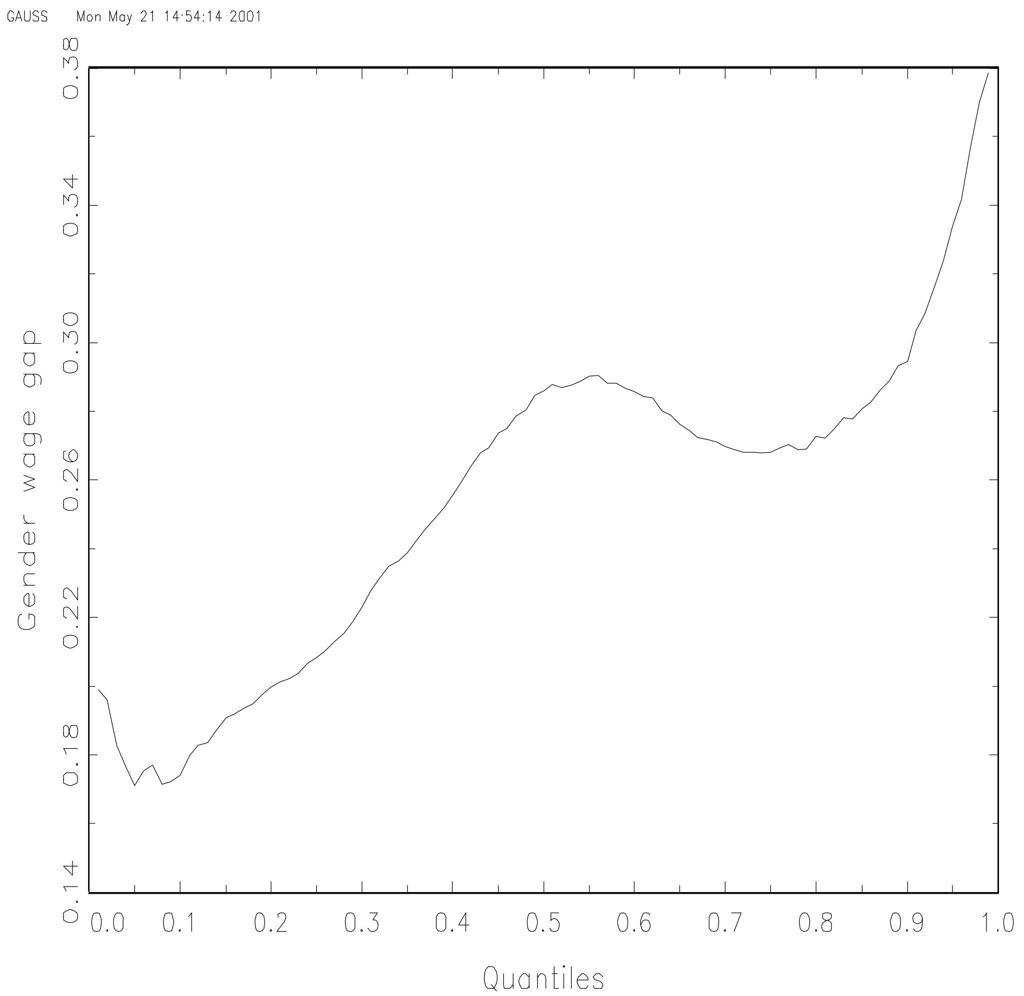

Figure 4: Gender wage gap at quantiles.

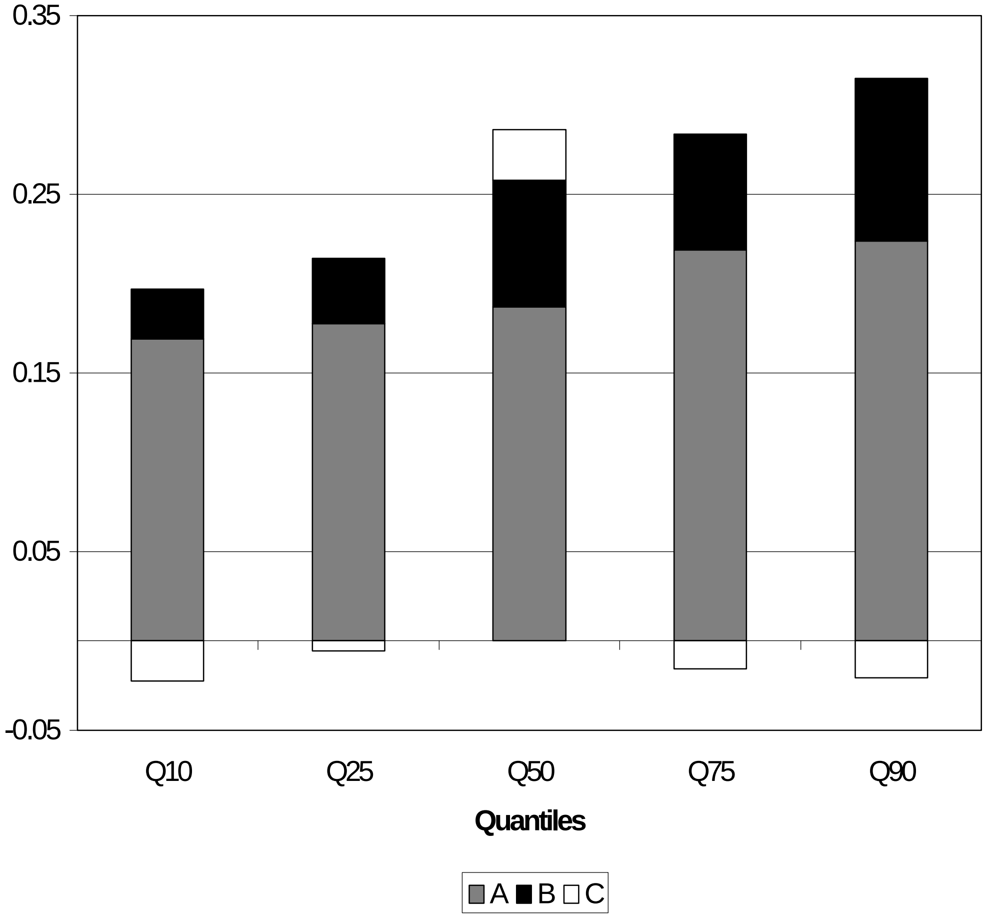

Figure 5: Gender wage wap decomposition.

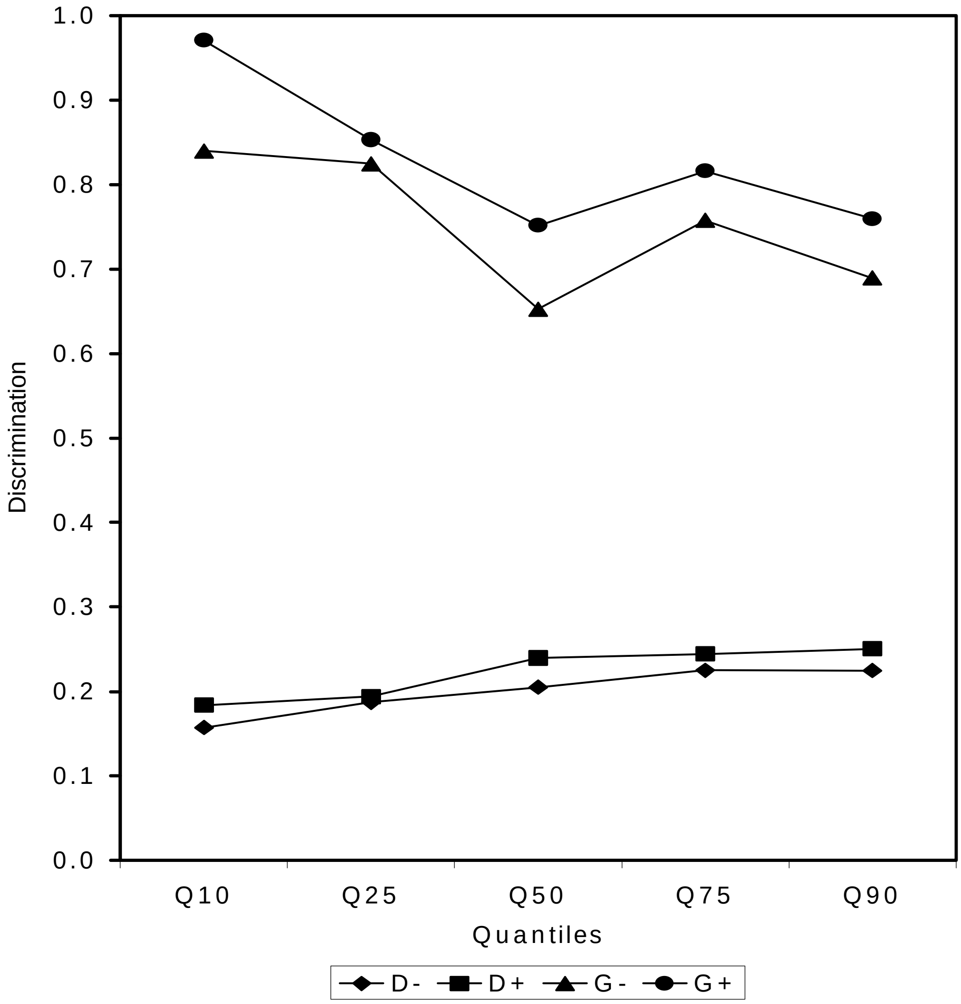

Figure 6: Absolute and relative discrimination.

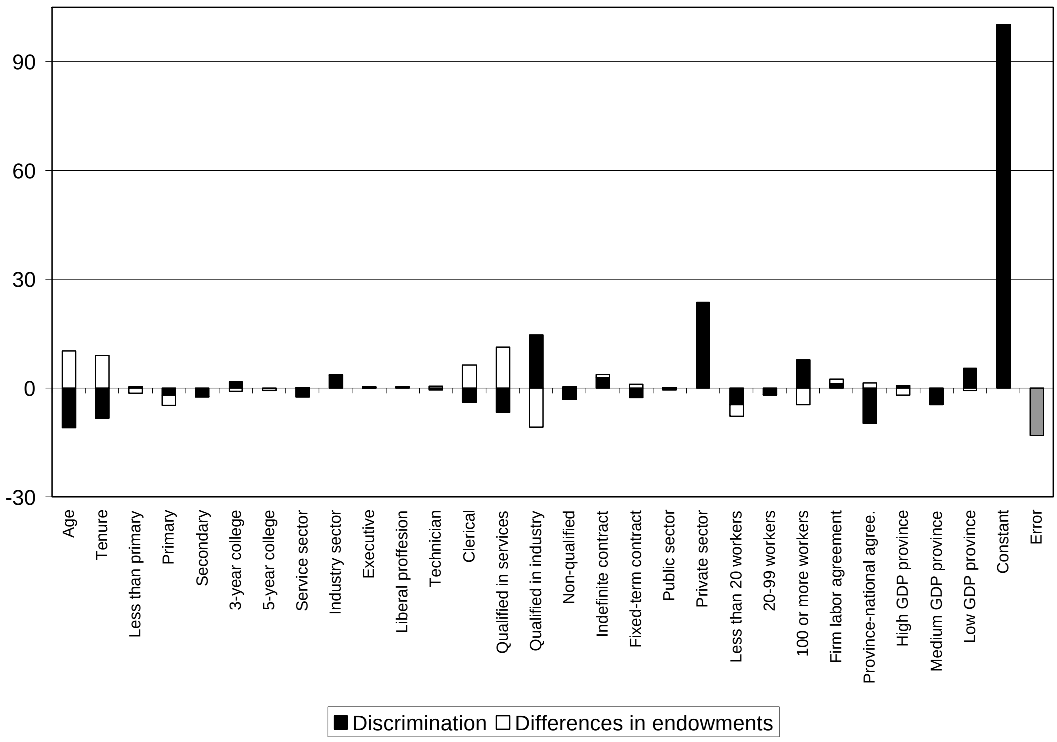

Figure 7: Decomposition by variable at the 0.10 quantile.

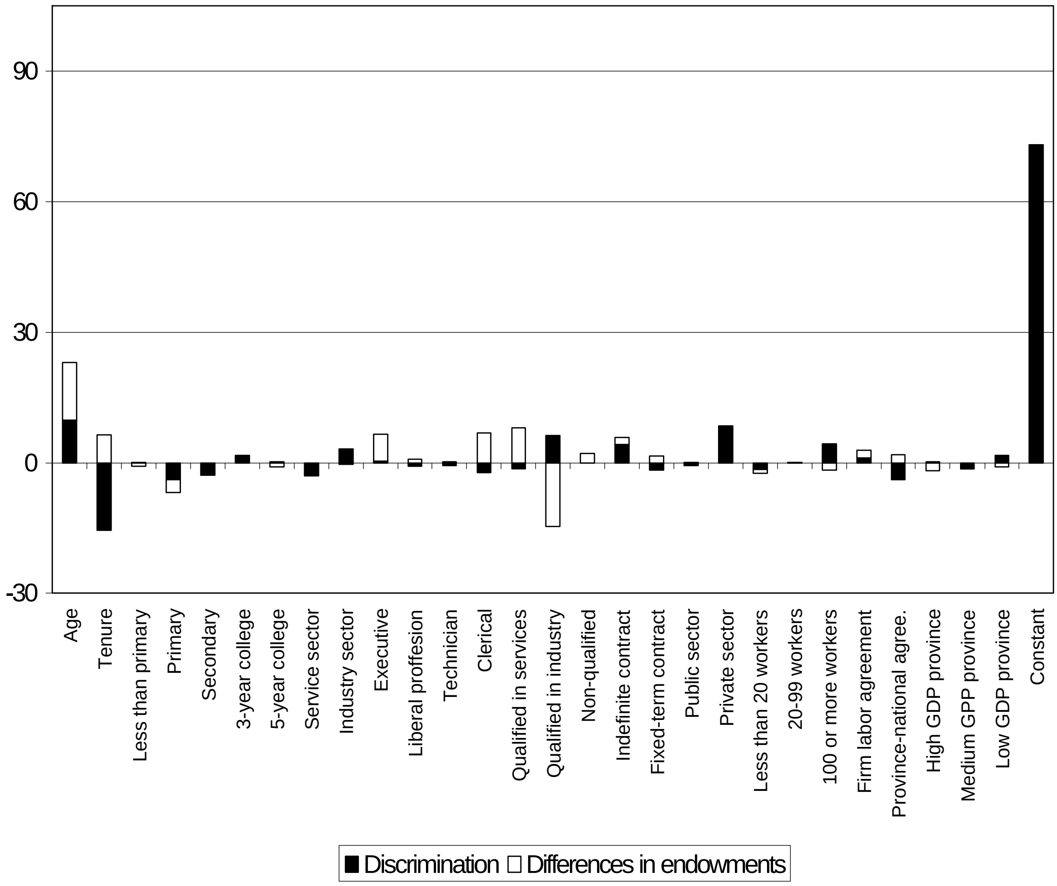

Figure 8: Decomposition by variables at the mean.

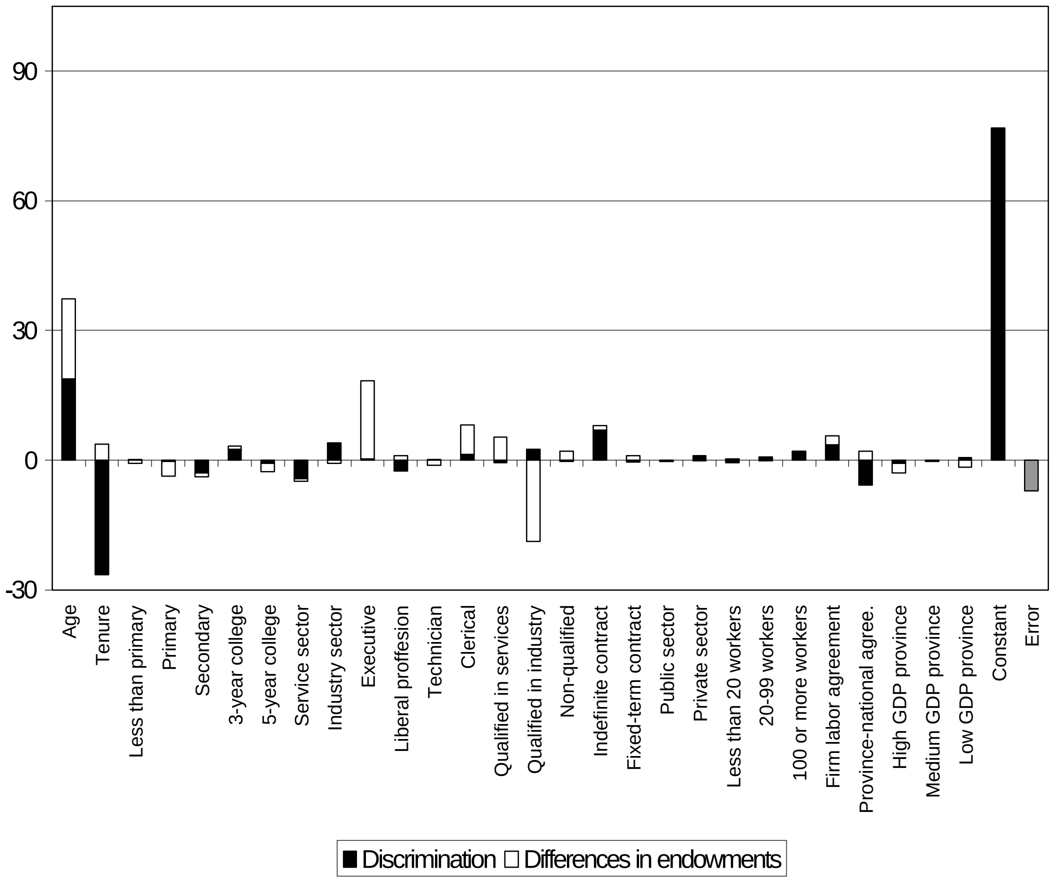

Figure 9: Decomposition by variable at 0.90 quantile.