Gender wage discrimination at quantiles

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Abstract

The literature on gender wage discrimination provides scalar measures of gender wage discrimination based on that part of the mean gender wage differential unexplained by differences in individual characteristics. While they give a general indication of what is the level of gender wage discrimination, they cannot identify whether discrimination is greater among high earners or among low earners. Furthermore, two populations may exhibit the same value of the scalar measure of discrimination while discrimination could be very differently distrubuted in the two populations. In this paper we extend Oaxaca's scalar measure to any quantile of the distribution of wages. This measure allows the analysis of how is discrimination distributed within a population and inter-population comparisons. We illustrate our proposed measure using the Spanish sample of the Survey of Wage Structure. We find that gender wage discrimination increases with the quantile index but as a fraction of the gender wage gap reaches a maximum at the nineth percentile.

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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 differentials should be due to differences in productivity between men and women. Gender wage discrimination takes place when equally productive workers are paid different wage rates. When there is discrimination, male-female wage differentials cannot be explained only in terms of differences in productivity. Since productivity is not observed by researchers, measures of discrimination usually adjust for all measurable characteristics that might be expected to affect productivity.[1]

In order to measure gender wage discrimination, the observed mean wage gap is typically split into two parts; the part due to differences in characteristics and the part due to differences in returns to these characteristics. The latter part is then used to calculate the extent of gender wage discrimination. There are several ways of conducting this decomposition of the observed gender wage gap, for instance Oaxaca (1973) provides a leading example.

Available measures of gender wage discrimination cannot be used to compare the degree of discrimination among two populations (countries or regions), as they are not scale free measures. To avoid this problem discrimination is measured relative to the total gender wage gap, a measure of discrimination that is invariant up to any affine transformation of wages.

While there is a prolific literature on gender wage differentials, most studies analyze differentials in average wages between men and women. Therefore, the measures of discrimination used in 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 different male and female mean wages are, in this paper we also study gender wage differences at other points of the distribution of wages. We investigate whether the degree of gender wage discrimination changes depending on whether 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 wage discrimination is greater among high earners or among low earners.

The measures of gender wage discrimination used in the literature summarize in a scalar descriptive statistic the degree of discrimination in the distribution of wages. There is a good reason for doing so, as a scalar statistic

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

may be used to infer the overall level of wage discrimination of the population under study. However, the use of a scalar statistic may not be appropriate for comparisons among two or more populations, as two wage distributions might exhibit the same value of the scalar statistic while discrimination could be very differently distrubuted in the two populations. This problem has been raised a large number of times in the studies of income inequality. Measures of income inequality such as the the popular Gini coefficient give a general view of the degree of income inequality, but two income distributions may have the same value of the Gini coefficient while income might be radically differently distributed. It is well known that two income distributions with the same Gini coefficient may have crossing Lorenz curves indicating differences in the distribution of income. We propose a measure of relative gender wage discrimination at each quantile of the distribution of wages which allows us to analyze how is discrimination distributed within the population. We also provide a graphical representation of our quantile measure of gender wage discrimination.

In addition, a quantile measure of gender wage discrimination may be used for policy evaluation. Governments implement policies aimed at reducing gender discrimination in general. These policies can be classified into two categories: those aimed at achieving higher female labor force participation and those trying to induce higher female presence in some occupations. Although not specifically targeted at reducing gender wage discrimination, these policies may have an effect on such discrimination. Arguably, policies might have different impacts at different quantiles of the distribution of wages if, for example, as a result of the policies implemented more women enter into low paid occupations. Therefore, it is necessary to measure gender wage discrimination at different quantiles to determine the indirect effect of such policies.

In order to measure gender wage discrimination, typically, the observed wage gap at the mean is split into two parts; the part due to differences in characteristics and the part due to differences in returns to these characteristics. Following this procedure, we split the wage gap at each quantile as the sum of two parts, differences in characteristics at each quantile and differences in returns to those characteristics at each quantile. We use quantile regression to estimate the returns to characteristics at various quantiles of the distribution of wages.[2] We illustrate our measure using the Spanish sample

[2]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. Quantile regression has also been applied to the study of gender wage discrimination: Reilly (1999) investigated the effect of Russia's

of the Survey of Wage Structure (SWS) of 1995. We find that relative gender wage discrimination is not constant across quantiles and reaches a maximum at the bottom of the distribution. This finding is in sharp contrast with the findings of García, Hernández and López-Nicolas (2001) who find that relative discrimination is maximal at the top of the distribution.

The rest of the paper is organized as follows. Section 2 deals with the measurement of the gender wage gap, outlines the typical procedure used to decompose the mean gender wage gap into differences in characteristics and differences in the returns to characteristics, extends that decomposition to any quantile and proposes two measures of gender wage discrimination. Section 3 illustrates the measures proposed making use of a sample of Spanish wages. Section 4 sumarises the conclusions. Appendix A explains how to compute sample counterparts of the theoretical measures described in the text. Appendix B describes the data set used and appendix C the main findings of the quantile regressions.

2 The measurement of gender wage discrimination

Gender wage differences may be due to discrimination, differences in productivity or both. In this section we study how to measure the gender wage gap and also how to decompose the gender wage gap into differences in characteristics (productivity) and differences in returns to characteristics (discrimination).

2.1 The gender wage gap

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 the gender wage gap is measured as the difference between the means of the distributions, that is, $E(w_m) - E(w_f)$. 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 $\mathsf{w}_{g\theta}$ the $\theta - th$ quantile of w_g, that is, $F(w_g \leq \mathsf{w}_{g\theta}) = \theta$. We will denote by $Q_\theta(\cdot)$

transition on the gender wage gap, Newell and Reilly (2001) extend the analysis to several ex-communist countries, Albrecht, Björklund and Vroman (2001) analyzed the gender pay gap in Sweden and García, Hernández and López-Nicolas (2001) studied gender wage discrimination in Spain.

the operator such that $Q_\theta(w_g) = \mathsf{w}_{g\theta}$. Therefore, the gender wage gap at quantile θ can be measured as $Q_\theta(w_m) - Q_\theta(w_f) = \mathsf{w}_{m\theta} - \mathsf{w}_{f\theta}$.

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 than women. Second, the gender wage gap is not an upper bound on discrimination. When women are more productive than men, but yet are paid less than men, discrimination is greater than the gender wage gap.

2.2 Discrimination at the mean

Next we describe the usual way of decomposing the gender wage gap as the sum of two terms, one reflecting differences in productivity and the other measuring discrimination. 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

$$E\left(w_g \mid x_g\right) = \beta_g' x_g.$$

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

$$w_g = \beta_g' x_g + u_g,$$

where $E\left(u_g \mid x_g\right) = 0$. 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

$$E\left(w_g\right) = \beta_g' E\left(x_g\right).$$

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

$$E(w_m) - E(w_f) = \beta_m' E\left(x_m\right) - \beta_f' E\left(x_f\right). \tag{1}$$

Adding and subtracting $\beta_m' E\left(x_f\right)$ to (1) we get

$$E(w_m) - E(w_f) = A_O + B_O \tag{2}$$

where

$$A_O = \left(\beta_m' - \beta_f'\right) E\left(x_f\right),$$

and

$$B_O = \beta_m'(E(x_m) - E(x_f)).$$

The resulting equation (2) decomposes the mean gender wage gap into 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 the wage difference due to different productive characteristics of males and females.[3]

Oaxaca's measure of discrimination is based on the discriminatory part of the decomposition[4]

$$D_O = \exp\left(A_O\right) - 1. \tag{3}$$

This 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. Moreover, Oaxaca's measure of gender wage discrimination is not scale free. Suppose (female and male) wages are multiplied by a positive constant, k. It follows that the discriminatory part of (2), A_O, is also multiplied by the same constant k. However, the quantity

$$G_O = \frac{A_O}{A_O + B_O}, \tag{4}$$

measures the proportion of the observed average wage gap due to different returns to the same endowments of productive characteristics. Notice that if we now multiply wages by a positive constant, both A_O and B_O get multiplied by the same constant but G_O remains unchanged. Therefore, this measure of discrimination is invariant up to any affine transformation of wages.

2.3 Discrimination at quantiles

When the researcher is concerned with measures of wage discrimination at locations other than 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

$$Q_\theta\left(w_g \mid x_g\right) = \beta_{g\theta}' x_g,$$

giving rise to the linear quantile regression model

$$w_g = \beta_{g\theta}' x_g + u_{g\theta}, \tag{5}$$

where $Q_\theta\left(u_{g\theta} \mid x_g\right) = 0$. 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.

[3]Subscript O refers to Oaxaca.

[4]See Oaxaca (1973) for details.

Taking the expected value of the quantile regression equation (5) conditional on the (log) wage being equal to its $\theta - th$ unconditional quantile, $w_g = \mathsf{w}_{g\theta}$

$$\mathsf{w}_{g\theta} = \beta'_{g\theta} E(x_g \mid w_g = \mathsf{w}_{g\theta}) + E(u_{g\theta} \mid w_g = \mathsf{w}_{g\theta}). \tag{6}$$

Expression (6) allows us to write the difference between male and female $\theta - th$ unconditional quantile wages as

$$\mathsf{w}_{m\theta} - \mathsf{w}_{f\theta} = A_\theta + B_\theta + C_\theta, \tag{7}$$

where

$$A_\theta = (\beta'_{m\theta} - \beta'_{f\theta}) E(x_f \mid w_f = \mathsf{w}_{f\theta}),$$

$$B_\theta = \beta'_{m\theta}(E(x_m \mid w_m = \mathsf{w}_{m\theta}) - E(x_f \mid w_f = \mathsf{w}_{f\theta})),$$

and

$$C_\theta = E(u_{m\theta} \mid w_m = \mathsf{w}_{m\theta}) - E(u_{f\theta} \mid w_f = \mathsf{w}_{f\theta}).$$

Equation (7) expresses the quantile gender wage gap as the sum of three terms. The first term, A_θ, measures the difference in returns to characteristics, usually considered as discrimination. The second term, B_θ, measures the differences in characteristics. The third term, C_θ, measures unexplained differences. This third term, which is not present in Oaxaca's decomposition, appears here because the conditional mean of the quantile regression's disturbance term need not be zero. Part of the gender wage gap at any given quantile is not explained by the quantile regressions.

Decomposition (7) has one attractive property. When decomposing the gender wage gap at quantile θ, gender wage differences in returns to characteristics are weighted according to the mean value of the characteristics at that quantile. For instance, gender differences in returns to secondary education at the tenth percentile are weighted by the (predicted) proportion of females with secondary education whose wage is at the tenth percentile. The decomposition has the drawback that there is an unexplained part. This unexplained part appears because the conditional quantile function is evaluated at a point which does not yield the unconditional quantile. There is, however, an infinite number of points where the conditional quantile function could be evaluated and it would return the unconditional quantile. Had we chosen to evaluate the conditional quantile function at any of these points, the decomposition would have been exact.

In what follows we propose an exact decomposition of the quantile gender wage gap. To do so we evaluate the conditional quantile function at a point where it yields the unconditional quantile. The decomposition will therefore be exact. The point where we evaluate the conditional quantile function is the closest point to the point where we evaluated the conditional quantile in the decomposition (7). The exact decomposition proposed is the exact decomposition closest to the more reasonable, but inexact, one advanced earlier.

Let us define the set of vectors $Z_{g\theta} = \{z \in \mathcal{Z} : Q_\theta(w_g) = \beta'_{g\theta} z\}$ where $\mathcal{Z}$ is the convex hull of the support of the joint probability density function of the explanatory variables in the wage equations. This set contains all vectors such that when the conditional quantile function is evaluated at any of these points it yields the unconditional quantile, that is, if $z \in Z_{g\theta}$ then $Q_\theta(w_g \mid x_g = z) = \mathsf{w}_{g\theta}$. Notice that, as long as the number of explanatory variables (other than the constant term) is greater than one, there is an infinite number of vectors in this set. Also notice that the vector of conditional means of the explanatory variables, $E(x_g \mid w_g = \mathsf{w}_{g\theta})$, does not usually belong to this set.

Next, we evaluate the conditional quantile function at a point z that solves

$$\min (z - x_{g\theta})'(z - x_{g\theta}) \qquad (8)$$
$$s.t. \quad z \in Z_{g\theta}$$

where $x_{g\theta} = E(x_g \mid w_g = \mathsf{w}_{g\theta})$. In words, the solution to this quadratic problem is the vector closest to $x_{g\theta}$ among those in $Z_{g\theta}$. Let $y_{g\theta}$ be the solution to the above minimization problem. The unconditional quantile wage can now be written as

$$\mathsf{w}_{g\theta} = \beta'_{g\theta} y_{g\theta},$$

and the gender quantile wage gap decomposition as

$$\begin{aligned} \mathsf{w}_{m\theta} - \mathsf{w}_{f\theta} &= A_\theta + B_\theta, \qquad (9)\\ A_\theta &= (\beta'_{m\theta} - \beta'_{f\theta}) y_{f\theta}, \\ B_\theta &= \beta'_{m\theta}(y_{m\theta} - y_{f\theta}). \end{aligned}$$

Absolute discrimination is in this case

$$D_\theta = \exp(A_\theta) - 1.$$

Notice that, D_θ is not scale free. Exactly as in the previous section, when we multiply wages by a constant k, the $\beta_{g\theta}$ coefficients get multiplied by the same constant, but the conditional means $E(x_g \mid w_g = \mathsf{w}_{g\theta})$ do not. Therefore, the discriminatory part of (9) A_θ gets multiplied by the same constant. However, the measure of relative discrimination at quantile θ

$$G_\theta = \frac{A_\theta}{A_\theta + B_\theta}$$

is invariant to any affine transformation.

2.4 Other measures of discrimination at quantiles

It is fair to say that our measure of gender wage discrimination at quantiles is not the first one proposed in the literature. García et al. (2001) constitutes a previous attempt to measure gender wage discrimination at quantiles. They use a measure of discrimination based on a decomposition of gender wage differences at conditional quantiles. They consider the gender wage gap at a given *conditional* quantile evaluated at the *unconditional* mean of the vector of explanatory variables. Their decomposition is

$$Q_\theta (w_m \mid x_m = E(x_m)) - Q_\theta (w_f \mid x_f = E(x_f)) = \beta'_{\theta m} E(x_m) - \beta'_{\theta f} E(x_f),$$
$$= \left(\beta'_{\theta m} - \beta'_{\theta f}\right) E(x_f) + \beta'_{\theta m}(E(x_m) - E(x_f)). \quad (10)$$

There are two reasons why we think it is more appropriate to measure discrimination at unconditional quantiles. First, a decomposition of conditional quantiles is in fact a decomposition of *predicted* wages, whereas a decomposition of unconditional quantiles is based on *observed* wages. Second, the García et al decomposition evaluates the vectors of characteristics of men and women at the same point, the unconditional mean, regardless of which quantile is considered. This might be inappropriate, as the following example illustrates. Most people with only primary education have wages in the lower part of the distribution of wages. Now, suppose we want to measure discrimination at the tenth percentile, where there is a high proportion of people with primary studies, and at the ninetieth percentile, where there is a low proportion of people with only primary studies. The García et al 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 tenth and ninetieth percentiles. However, it might be considered more appropriate to weight the 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.

3 The empirical results

The data come 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 information on individuals working for firms with ten or more employees from all sectors and provinces.

To give an idea of how representative the sample is, workers at firms with ten or more employees accounted for 70.75% (72.95% of men and 66.74% of women) of the total working population in Spain in October of 1995.[5]

3.1 The gender wage gap

The usual procedure for measuring the male-female wage gap is to consider the difference between the average male wage and its female counterpart. In our sample, the average male hourly wage was $\overline{W}_m = 1255.02$ Spanish pesetas, whereas the female hourly wage was $\overline{W}_f = 947.80$. Therefore, the male-female average wage differential was $\overline{W}_m - \overline{W}_f = 307.22$ pesetas.[6] When we do the same calculations but consider log hourly wages the male-female average wage gap differential turns out to be $\overline{w}_m - \overline{w}_f = 6.9815 - 6.7266 = 0.2549$, where $w_g = \ln W_g$. This gap may be due, at least partially, to differences in productivity between the population of males and females in our sample.

Figure 1 shows nonparametric estimates of the density functions of male and female (log) hourly wages.[7] The male wage density is displaced rightward with respect to the female wage distribution, indicating a non negligible gender wage gap. The gender gap is better viewed in Figure 2, which shows 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 3 plots the observed gender wage gap as a function of the quantile index. The gender gap is decreasing within the first 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 may also change when measured at different quantiles.

3.2 Returns to characteristics

Following the usual practice in the field, 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 firm size, the type of labor agreement that settles wages in the firm, whether the firm is publicly

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

[6] 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 1.70 US dollars.

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

or privately owned, and the occupation and type of contract the individual has. Except for age and tenure, all explanatory variables are categorical.[8] We estimate separate wage equations for men and women.[9] For the shake of brevity, a complete description of the quantile regression results at selected quantiles is reported in appendix C. The general result is that returns to characteristics do change with quantiles both for men and women.

3.3 Discrimination

According to the results of Table 1, Oaxaca's measure of absolute discrimination is $\widehat{D}_O = 0.211$. This figure tells us that the observed male-female average wage ratio is 21% higher than that which 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. Discrimination relative to the gender wage gap yields a value of $\widehat{G}_O = 0.751$. Seventy-five percent of the average gender wage gap is explained by differences in returns while twenty five percent is explained by differences in observed characteristics.

Using the estimation procedure outlined in Appendix A we have computed measures of gender wage discrimination at 99 percentiles of the distribution of wages. Figure 4 plots our measure of absolute gender wage discrimination. Except at the bottom and top of the wage distribution, absolute discrimination increases. The part of the gender wage gap due to differences in returns to characteristics is increasing for most of the wage range. At the median, absolute discrimination is $\widehat{D}_{0.5} = 0.207$ very close to Oaxaca's measure at the mean. However, absolute discrimination ranges from a minimum value of $\widehat{D}_{0.03} = 0.168$ at the third percentile to a maximum value of $\widehat{D}_{0.89} = 0.255$ at the 89-th percentile.

Figure 5 plots our quantile measure of relative gender wage discrimination at 99 percentiles. Discrimination is very high at low quantiles, reaching a maximum of 98.6% at the 9-th percentile, then falls until we reach the median, increases until the 81th percentile and falls again to reach the min-

[8]As pointed out by Oaxaca and Ransom (1999), the presence of dummy variables may pose a problem when comparing returns to a particular explanatory variable for men and women. In order to solve this problem we use the procedure suggested by Gardeazabal and Ugidos (2002). This involves including all dummies, i.e. leaving out no reference group, and imposing the identification restriction that the sum of the coefficients on each set of dummies is zero.

[9]We also estimate a pooled regression including a gender dummy and interactions with all the explanatory variables and test if the estimated coefficients for men and women are equal. We always reject the null hypothesis that the coefficients are equal at standard levels of significance.

imum value of 57.5% at the 99-th percentile. Accordingly, relative gender wage discrimination seems to be very unevenly distributed, something we cannot say from Oaxaca's discrimination coefficient. Figure 5 also tells us that at the bottom of the wage distribution individual characteristics are very similar between men and women and therefore most of the gender wage gap is accounted for by the discriminatory part. At the top of the distribution, however, differences in characteristics explain a higher fraction of the gender wage gap and relative discrimination is lower.

The finding of a non monotonically decreasing measure of relative discrimination contrasts with the results of García et al (2001) who find that both absolute and relative discrimination are maximal at the top of the distribution. 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 García et al 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, in both absolute and relative terms, as in García et al. Hence, the choice of discrimination measure determines the result. As argued above, there are two reasons for preferring our measure of discrimination. First, García et al's measure is based on a decomposition of the predicted (rather than observed) gender wage differential. Second, their measure weights returns differentials equally at all quantiles, regardless of the density of population at any particular quantile. Our results suggest that gender wage discrimination represents a lower fraction of the gender wage gap of high earners than of low earners.

4 Conclusions

Measures of gender wage discrimination summarize in a scalar statistic the overall level of discrimination within a given population of workers. However, gender wage discrimination may be very unevenly distributed within the population. Furthermore, two populations of workers could exhibit the same value of a scalar measure while discrimination could be very differently distributed. In this paper we have developed a new method of measuring gender wage discrimination at different quantiles of the distribution of wages. This method allows us to analyze how is discrimination distributed within a population and also allows us to make inter population comparisons.

Using a sample of wages for Spain we reach the following conclusions. First, there are quantitatively important differences in returns at different locations of the distribution of wages. Second, when we measure discrimination in absolute terms, it increases as we move upward in the distribution of wages, whereas discrimination relative to total quantile gender wage differential is highest at low quantiles.

It remains an open question whether our finding that relative discrimination is lower at the top part of the distribution of wages is specific to the Spanish sample used in this paper or, perhaps, a stylized fact shared by samples from other countries. But suppose for a moment that our finding was a generalized one and discrimination was lower among high wage earners in all countries. This implies that, if economic growth leads to a distribution of wages with more density at the upper quantiles of the wage distribution, economic development should be accompanied by a lower degree of (relative) gender wage discrimination.

Appendix A: Estimation

In this appendix we outline a series of steps needed to how to obtain a sample counterpart of the gender quantile wage difference decomposition .

1. First, an estimate of the $\theta - th$ unconditional quantiles of (log) wages, say $\overline{\mathrm{w}}_{g\theta}$, is given by the $[\theta N_g] - th$ order statistic, where N_g is the number of individuals in the sample of gender g and $[\cdot]$ is the closest integer operator.

2. Second, we use a Koenker and Bassett (1978) estimator of the quantile regression parameters, $\widehat{\beta}_{g\theta}$. This estimator solves

$$\min_{\beta_\theta} \sum_{i=1}^{N} \rho\left(u_{\theta i}\right)$$

   where $\rho\left(a\right) = \left(\theta 1\left(a \geq 0\right) + \left(1 - \theta\right) 1\left(a < 0\right)\right)\left|a\right|$. Under some regularity conditions, the Koenker and Bassett (1978) estimator has a normal asymptotic distribution. In this paper we use the Design Matrix Bootstrap (DMB) method to estimate the covariance matrix of the vector of parameter estimates.[10]

3. Third, the estimation of $x_{g\theta}$ is covered in two parts as the components of the vector of characteristics will typically contain many binary variables and some continuous variables. Let x_{gj} be the $j - th$ element of x_g and Let $x_{g\theta j}$ be the $j - th$ element of $x_{g\theta}$.

   (a) If x_{gj} is a binary variable 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 use 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

$$\widehat{x}_{g\theta j} = \Phi(\widehat{\alpha}_j + \widehat{\delta}_j \overline{\mathrm{w}}_{g\theta}).$$

[10]See Buchinsky (1994) for details.

(b) If x_{gj} is a continuous variable 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

$$\widehat{x}_{g\theta j} = \widehat{\alpha}_k + \widehat{\delta}_k \overline{\mathrm{w}}_{g\theta}.$$

4. Fourth, the point $\widehat{y}_{g\theta}$ where the conditional quantile is evaluated is found as the solution to

$$\min_z (z - \widehat{x}_{g\theta})'(z - \widehat{x}_{g\theta}) \tag{11}$$

$$s.t. \begin{cases} \overline{\mathrm{w}}_{g\theta} = \widehat{\beta}'_{g\theta} z \\ 0 \leq z_j \leq 1 \quad j = 1, 2, ..., K. \end{cases}$$

where $z = (z_1, z_2, ...z_J)'$, K is the number of dummy variables and J is the number of explanatory variables in included in the conditional quantile regressions, with $K < J$.

5. Fifth, the estimates of A_θ and B_θ are

$$\widehat{A}_\theta = (\widehat{\beta}'_{m\theta} - \widehat{\beta}'_{f\theta})\widehat{y}_{f\theta},$$

$$\widehat{B}_\theta = \widehat{\beta}'_{m\theta}(\widehat{y}_{m\theta} - \widehat{y}_{f\theta}).$$

Appendix 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 must 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 provides no data in order to preserve anonymity. Thus, if the researcher wants a very fine description of 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 the six variables. In particular, we aggregate the seventeen Spanish regions into three categories, low, medium and high GDP.[11] We aggregate the nine sectors available into two: services and industry, with the latter including construction. We aggregate the five firm-size groups into three categories of 10 to 19, 20-99 and 100 or more employees. The five types of collective agreement available are merged into two: at firm or establishment level and at sectorial, provincial or national level. We do not consider the "product market" variable in our request. Finally, we merge the four types of "state ownership" into two: private and others, with the latter including public, mostly public and others. In addition to this, we aggregate the 68 education groups into five.[12] We also aggregate the two-digit occupations of the CNO-94 into seven groups.[13] The sample size is 177,114. We have 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 their wages (25) and those whose reported wage was less than 100 pts/hour (151). The final sample size is 164,270: 129,061 men and 35,209 women.

Table B1 shows the mean and quantiles of wages, age and tenure. The average male wage per hour is 1,255 pesetas, whereas the average female wage per hour is not quite 948 pts. The average female wage is 75.5% of the average male wage. The female to male wage ratio varies over the wage distribution (10 percentage points between the lowest and the highest quantile). We observe that at the 10^{th} percentile the female wage rate is 84% of that of males. The ratio decreases until we reach the median, 75.1%, then increases slightly to 76.5% at the 75^{th} percentile and goes down again, reaching its lowest level at the 90^{th} percentile, 74.5%. This simple ratio shows us big differences in the gender wage gap over the wage distribution.

Women are four years younger than men on average. The gender age difference increases as we move from the lowest to the highest quantile (from 2 to 6 years). Women have, on average, about two and a half years less tenure than men. Gender tenure differences increase from one year at the 10^{th} percentile to three years at the 90^{th}percentile.

[11] Low GDP regions are Andalusia, Cantabria, Castilla-La-Mancha, Castilla-León, Extremadura, Galicia and Murcia. Medium GDP regions are Aragón, Asturias, Canary Islands, Comunidad Valenciana and La Rioja. High GDP regions are Balearic Islands, Catalonia, Madrid, Navarra and the Basque Country.

[12] Less than primary studies, primary studies, secondary studies (including high school and three-year vocational studies), three-year college education (also including five-year vocational studies) and five-year college education (including Master's diplomas and Ph.D.'s).

[13] Executives, professionals, technicians, clerical workers, skilled workers in the services sector, skilled workers in industry or construction and unskilled workers.

Looking at Table B2 we find that women are also more highly educated on average than men. Our data also show big differences between men and women in occupations. More than 40% of women work as clerical and skilled workers in the service sector while 51% of men work as skilled workers in the industry and construction sectors. Fixed-term contracts are more frequently used for women (29%) than for men (23%). The evidence presented by Jimeno and Toharia (1993) shows that workers with indefinite contracts earn 9 to 11 percent more than those with fixed-term contracts. De la Rica and Felgueroso (1999) find that this difference increases with qualification. Over 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. Finally, 46% of women and 39% of men live in "high GDP" regions.

Appendix C: Regression estimates at selected quantiles

The conditional mean equation is estimated by OLS. The conditional quantile equations are estimated by quantile regression at quantiles $\theta = \{0.10, 0.25, 0.50, 0.75, 0.90\}$. The results are shown in Table C1 for men and C2 for women. Looking at the quantitative results of tables 1a and 1b, we observe that all the variables are significant at the 5% level and the estimated coefficients take the expected signs. We next describe the results in more detail.

Returns to age are positive and higher at top quantiles, for both 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 for both 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} percentile for secondary education). However, the return to primary education for men decreases as the quantile increases (again, except at the 25^{th} percentile). Returns to secondary or higher education for women decline at the 25^{th} and 50^{th} percentiles and increase afterwards. For women, returns to 3-year college studies are equal to those to secondary education from the 10^{th} to the 75^{th} percentile, while they are lower at the 90^{th} percentile, a striking difference with respect to men. Comparing the results of the quantile regressions with those of the mean regression we find higher returns to 5-year college education for women than for men at the 10^{th} and 90^{th} percentiles, and lower returns for women than for men at the other quantiles, while we find a similar return to 5-year college education at the mean for men and women.

Years of tenure in the firm increase workers' wages. The return to an additional year of tenure is higher for women than for men at all quantiles and at the mean. We also observe that the return to tenure decreases steadily across the higher quantiles. Furthermore, we find that this decrease is more pronounced for men than for women.

As expected, we observe that the wage increases with the rank of occupation for both men and women. On average, men earn relatively more than women as executives and skilled workers in the industry sector than as unskilled workers. The contrary is observed for all other occupations (the professions, technical and clerical jobs and skilled jobs in the service sector). Looking at the quantile regressions results, we also observe that men earn more than women as executives and skilled workers in industry at all quantiles. In addition, we find that men earn more than women also as skilled workers, clerical workers and technicians at the 75^{th} and 90^{th} percentiles.

Our results show that male and female workers who have an indefinite labor contract earn higher wages than those who have a fixed-term contract. The difference in wages between the two types of labor contract is much wider for the upper quantiles. If we look now at gender differences 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 especially for women. For women, the public sector premium is much higher at the lower quantiles. The gender differential in returns shrinks at higher quantiles.

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

We find that low-level (firm and establishment) collective bargaining results in 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 a U-shaped pattern as we go from the 10^{th} to the 90^{th} percentile.

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.

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Table 1: Gender wage gap decomposition.

$\overline{w}_m - \overline{w}_f$	$\widehat{A}_O$	$\widehat{B}_O$	$\widehat{D}_O$	$\widehat{G}_O$
0.255	0.191	0.064	0.211	0.751

$\overline{w}_m - \overline{w}_f$	= gender wage gap
$\widehat{A}_O$	= differences in returns to endowments.
$\widehat{B}_O$	= differences in endowments.
$\widehat{D}_O$	= Oaxaca's measure of discrimination.
$\widehat{G}_O$	= relative discrimination.

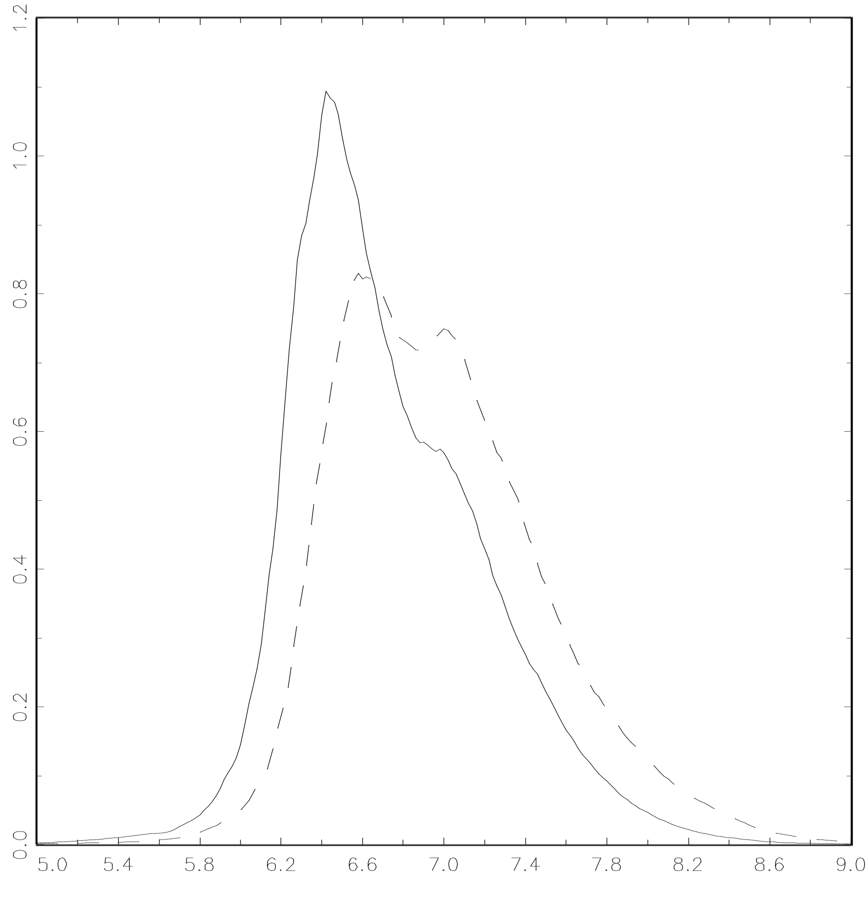

Figure 1: Male (broken) and Female (solid) wage densities.

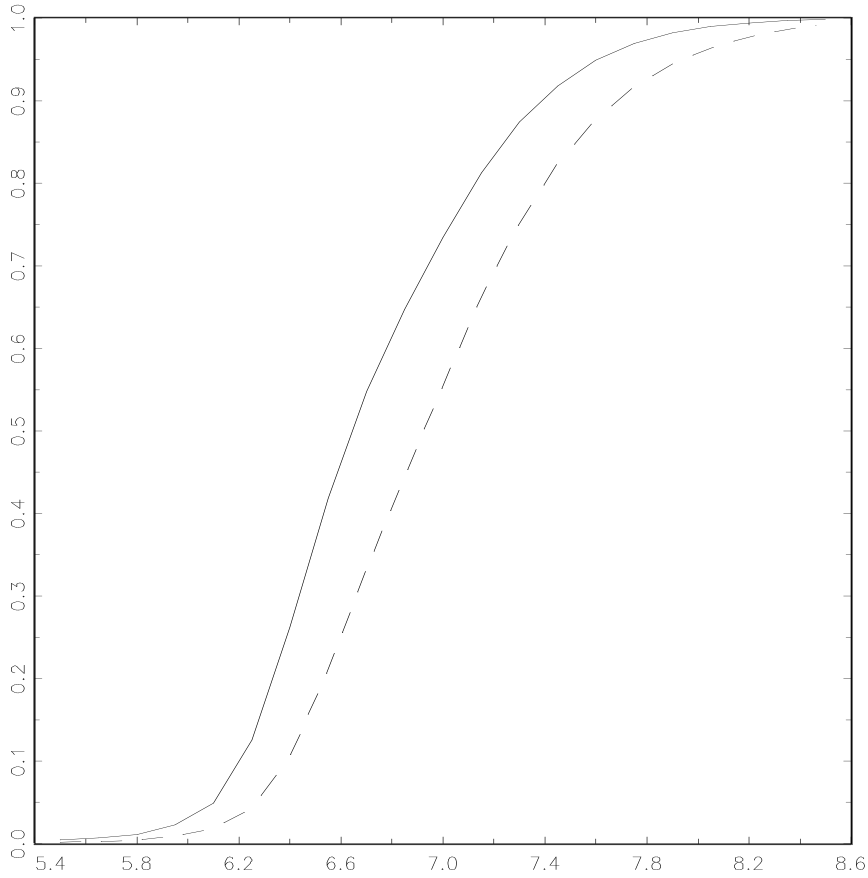

Figure 2: Male (broken) and female (solid) wage distribution functions.

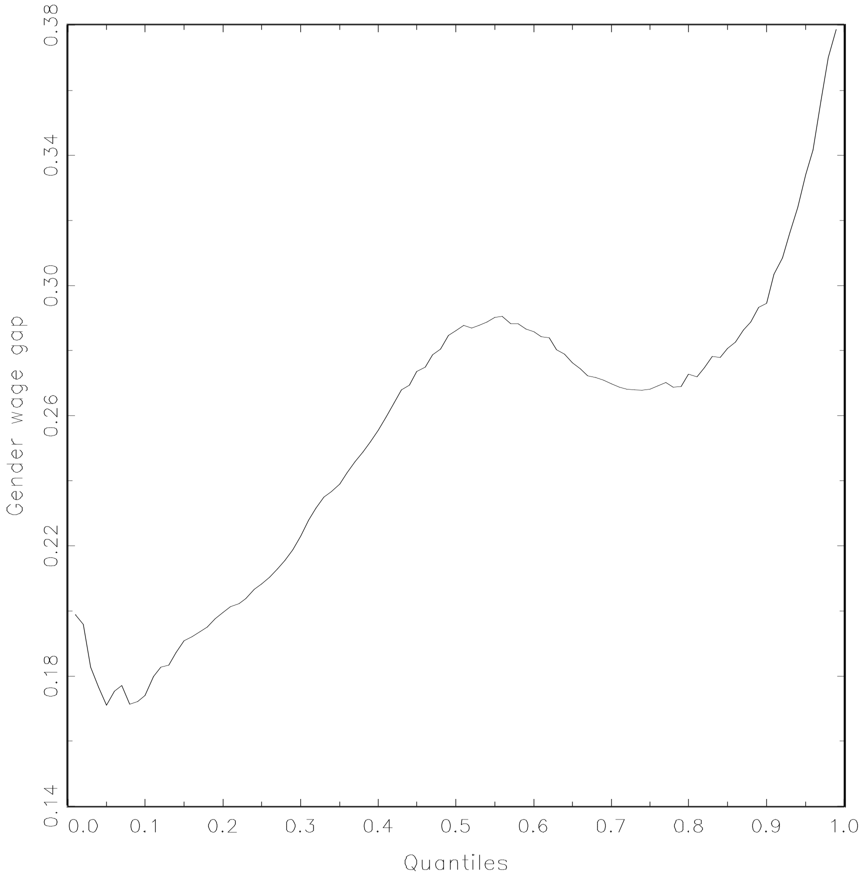

Figure 3: Gender wage gap at quantiles.

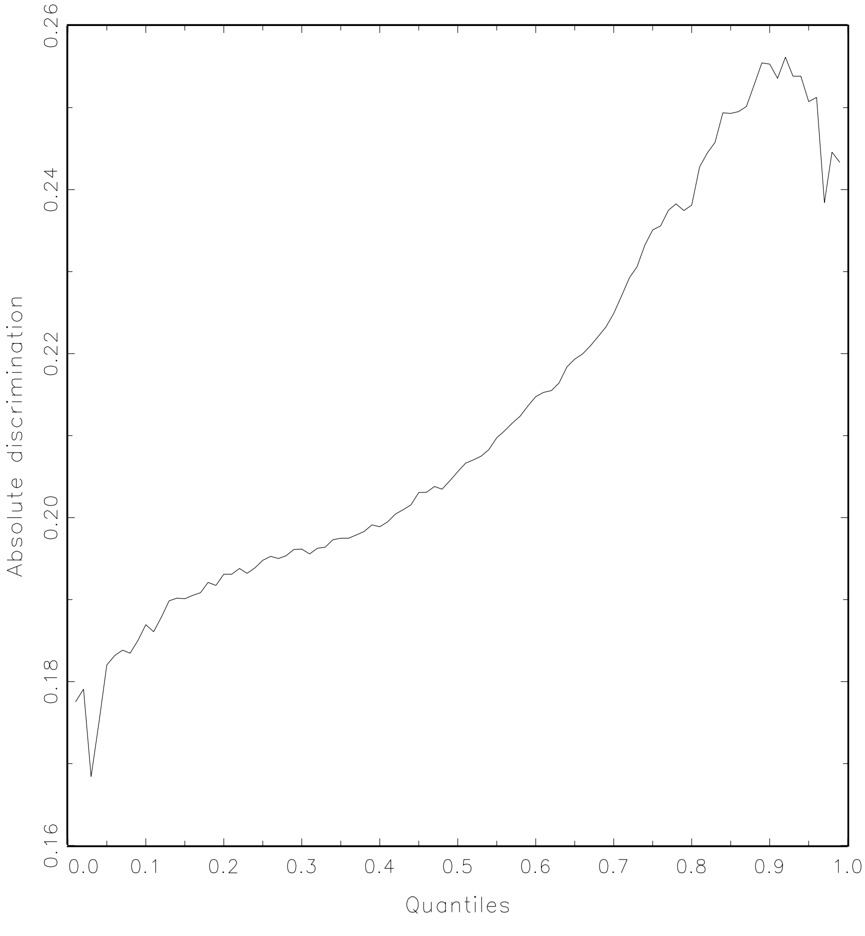

Figure 4: Absolute discrimination at quantiles.

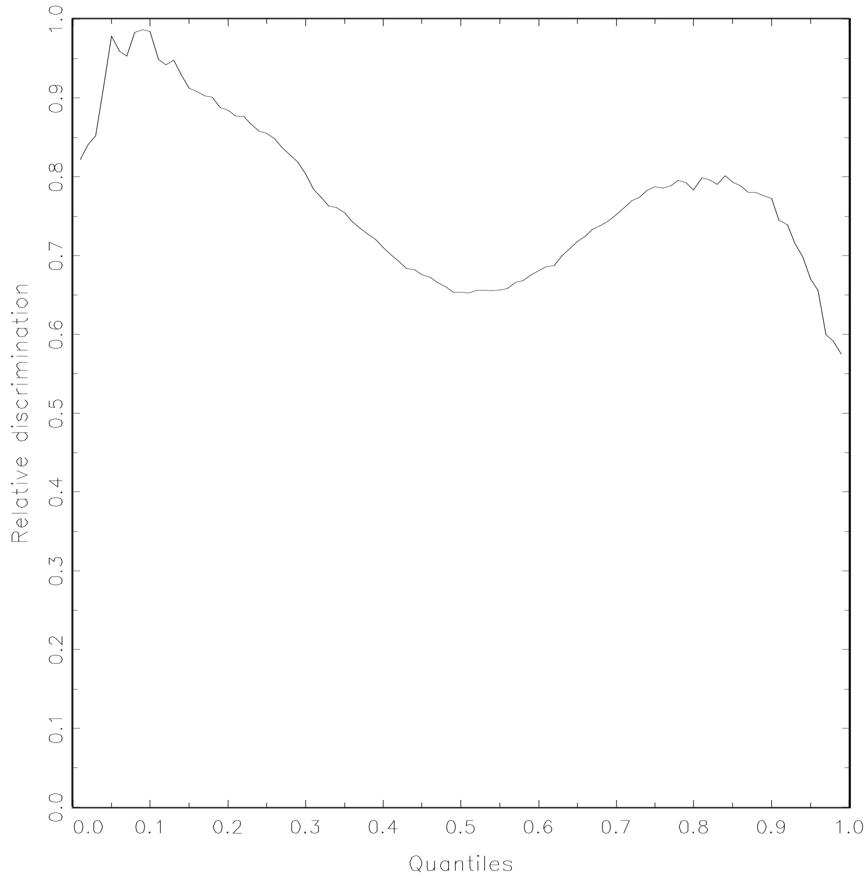

Figure 5: Relative discrimination at quantiles.

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

	Quantiles					Mean
Variables	$\theta = 10$	$\theta = 25$	$\theta = 50$	$\theta = 75$	$\theta = 90$	
			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
Professional	0.055	0.044
Technician	0.111	0.105
Clerical worker	0.093	0.277
Skilled (services)	0.068	0.163
Skilled (industry)	0.513	0.266
Unskilled	0.111	0.131
Services	0.308	0.457
Industry and const.	0.692	0.543
Fixed-time contract	0.231	0.286
Indefinite 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	0.218
Provincial or national	0.711	0.782
High GDP province	0.388	0.464
Medium GDP province	0.252	0.230
Low GDP province	0.360	0.306

Table C1: Returns to Men's characteristics.

	$\theta = 0.10$	$\theta = 0.25$	$\theta = 0.50$	$\theta = 0.75$	$\theta = 0.90$	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 than 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)
Professional	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 worker	-0.0812	-0.0936	-0.1044	-0.1003	-0.0793	-0.0939
	(0.0042)	(0.0030)	(0.0031)	(0.0042)	(0.0054)	(0.0032)
Skilled 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)
Skilled 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)
Unskilled	-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 C1: Returns to Men's characteristics (Continued).

	$\theta = 0.10$	$\theta = 0.25$	$\theta = 0.50$	$\theta = 0.75$	$\theta = 0.90$	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 than 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 or 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 GDP	-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 C2: Returns to women's characteristics.

	$\theta = 0.10$	$\theta = 0.25$	$\theta = 0.50$	$\theta = 0.75$	$\theta = 0.90$	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 than 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)
Professional	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 worker	-0.0492	-0.0634	-0.0825	-0.0991	-0.0910	-0.0730
	(0.0068)	(0.0050)	(0.0067)	(0.0080)	(0.0114)	(0.0043)
Skilled 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)
Skilled 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)
Unskilled	-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 C2: Returns to women's characteristics. (Continued)

	$\theta = 0.10$	$\theta = 0.25$	$\theta = 0.50$	$\theta = 0.75$	$\theta = 0.90$	mean
Indef. contract	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 contract.	-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 than 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 or 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 GDP	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)