Ceilings and Floors:
Gender Wage Gaps by Education in Spain[*]

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ABSTRACT

This paper analyses the gender wage gaps by education throughout the wage distribution in Spain using individual data from the ECHP (1999). Quantile regressions are used to estimate the wage returns to the different characteristics at the more relevant percentiles and a suitable version of the Oaxaca-Blinder decomposition is then implemented to estimate the component of the gender gap not explained by different characteristics. Our main findings are two-fold. First, in contrast with the steep pattern found for other countries, the flatter evolution of the gap found in Spain hides a composition effect when the sample is split by education. On the one hand, for the group with college/tertiary education, we find a higher unexplained gap at the top than at the bottom of the distribution, in accordance with the conventional *glass ceiling* hypothesis. On the other, for the group with lower education, the gap is much higher at the bottom than at the top of the distribution. We label this novel pattern as *glass floors* and argue that it is due to statistical discrimination exerted by employers in view of the low participation rate of women in this group. Such a hypothesis is confirmed when using the panel structure of the ECHP.

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1. Introduction

It is a widely documented fact that men earn higher wages than women even after controlling for measurable characteristics related to their productivity (see, e.g., Blau and Kahn, 1997). There is an extensive literature about this topic based on the comparison of average (logged) wages, where measures of the so-called gender wage gaps (gender gap in short) are typically interpreted as estimates of discrimination at the mean of the observed distribution of wages. Nonetheless, the analysis of the gender gap at other points of the distribution has drawn much less attention.[1] Lately, however, there has been a growing interest about how this gap evolves throughout the distribution in order to test whether wage discrimination is greater among high earners than among low earners, in line with the so-called *glass ceiling* hypothesis.

In this paper, inspired by the approach advocated by Albrecht et al. (2003) about the existence of glass ceilings in Sweden, we derive quantile measures of the gender gap in Spain at the end of the 1990s. This is an interesting issue, since Spain, like some other Southern-Mediterranean countries (e.g., Greece or Italy but not Portugal), still has a much lower female participation than the Nordic countries and therefore patterns of women's achievements in the labour market are bound to differ markedly from those found there.[2] Indeed, the evidence we provide supports this view: the gender gap in Spain is much flatter than in Sweden. And, moreover, this pattern hides a composition effect when one splits

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[1] Well-known examples of this type of research are Chamberlain (1994) and Buchinsky (1994, 1996, 1998) who use quantile regressions to analyze the wage structure in the U.S. An application of this method to Spain can be found in Abadie (1997) and more general applications in Fitzenberger et al. (2001). More recently, such estimation techniques have been used to study gender wage discrimination in several former communist countries (Newell and Reilly, 2001) and in Sweden (Albrecht et al., 2003). As regards the latter topic in Spain, there are two related studies to ours. On the one hand, García et al. (2001), using the 1991 *Encuesta de Conciencia, Biografía y Estructura de Clase*, control both for the endogeneity of education as well as for the selection of women into the labor market and conclude that the discrimination component, in absolute and relative terms, is higher at the top of the wage distribution. On the other, Gardeazabal and Ugidos (2002), who make use the 1995 *Encuesta de Salarios*, also find that the raw gender gap increases along the distribution but, by contrast, estimate that the discrimination component, in relative terms, is larger at the bottom of the distribution.

[2] The Spanish female activity rate (% of population aged 15-64) in 2001 was 50.7% whereas it reached 75.7 % in Sweden and 60.2% in the EU. By educational levels, the corresponding rates in Spain were 80.4% and 48.0% for the women with tertiary education and less than tertiary education (84.6% and 68.3% in Sweden), respectively (see OECD, 2002). Indeed, the group of Spanish working women is formed by very heterogeneous cohorts. Since the 1980s, female participation has surged (from 33.3% in 1980 until 50.7% in 2001) mainly due to the increase in higher education and the reduction in fertility rates (see, e.g., Arellano and Bover, 1995).

the sample of workers by education. In this respect, as will become clear below, we find it crucial to distinguish between workers with high (college/tertiary, henceforth denoted as H-group) and lower (primary/secondary, denoted as L-group) educational attainments in contrast to most of the available studies on this topic. The reason for doing so is that the behavior of the gap throughout the distribution differs markedly and in an interesting fashion between both groups of workers.

Using the 1999 (6th. wave) of the European Community Household Panel (ECHP, henceforth) for full-time workers, Figure 1a plots the gender gap (in terms of the differences of logged gross hourly wages of male and female workers) in Spain throughout the distribution, together with the mean gap (dashed line). As can be observed, there is a decreasing trend that becomes stable around the 60th percentile to then increase sharply at the top quantiles. As expected, the gender gap at the mean differs notably from the gap at the various percentiles. This non-monotonic evolution, however, stands in sharp contrast to the one found for Sweden (see Figure 1b) where the raw gap increases by 35 percentage points from the bottom to the top of the (log) wage distribution giving rise to the well-known glass ceiling phenomenon documented in Albrecht et al. (2003).

[Figures 1a, 1b, 1c, 1d about here]

Figures 1c and 1d in turn depict the corresponding quantile gender gaps for the L and H groups. Inspection of the graph for the H-group shows that it is increasing and therefore fits well with the glass ceiling hypothesis. By contrast, it is decreasing for the L-type workers. Aggregation of both types of workers therefore gives rise to the flatter and non-monotonic pattern depicted in Figure 1a. Thus, there seems to be an ″educational composition effect ″ that deserves greater scrutiny. Interestingly, northern and central European countries, such as Denmark and the U.K. (Figures 2a and 2b), exhibit a monotonically increasing gap, while in southern European countries with low female participation, such as Greece and Italy (Figures 2c and 2d), the behavior is more irregular and, when splitting the sample by education, resembles the one found above for Spain. [3]

[Figures 2a, 2b, 2c, 2d about here]

[3] The gender gaps for Denmark, France, Greece and Italy also correspond to the 1999 wave of the ECHP. The Swedish gender gap is reproduced from Figure 1 of Albrecht et al. (2003) which corresponds to 1998 with the data coming from *Statistics Sweden* (SSW). Activity rates by education in those countries can be found in Table A1 in the Appendix.

Two possible explanations arise in order to reconcile these divergent patterns by educational attainments:[4]

1. For the L-type women, female activity rates are still much higher in northern and central European countries than in most southern European ones, despite the catching-up process in participation that has taken place during the last two decades in the latter countries (see Table A1). To the extent that less-educated women's careers in those labour markets suffer from frequent interruptions in the latter countries - due to societal discrimination in family duties or religious beliefs - employers may use statistical discrimination resulting in lower wages than men´ s in the lower part of the wage distribution which typically corresponds to entry jobs in the labour market. This, for instance, can be the case if there is specific training at the early stages of a job whose financing is shared by employers and workers. The proportion paid by the worker is bound to be smaller for men than for women, given the higher propensity to quit of the latter. As their job tenure expands, however, women become more reliable to employers and their wages converge to men's. To stress its difference with the glass ceiling phenomenon, we will label this declining pattern as *glass floor* in what follows. [5]

2. *H-type women* have participation rates only slightly below men ´s even in the Southern Mediterranean countries (see Table A1) and bound to be considered much more stable in their jobs, given the human capital investment that they have undertaken. In line with their presumed higher commitment, their wages will be similar to men's wages at their entry jobs in the lower part of the distribution. As we move up, however, women's wages may fall below men's if the traditional 'glass ceiling' phenomenon holds. A well-known rationale for this pattern is the so-called 'dead-end' argument whereby women are promoted less frequently because they perform jobs with less opportunities of promotion. For example, Polachek

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[4] Another possible explanation could arise from some form of unobserved heterogeneity affecting L-type women in relation to their male counterparts (see more about this in section 5). Further, the OECD (2002) warns about the possibility of measurement errors in the survey stemming from the fact that the interviewed persons provide direct information about their own wages, rather than their employers, as is the case with matched employer-employee data. If those earning more, mainly men, have a larger propensity to understate their wages, the gap for the higher quantiles would be underestimated. Although this argument could imply a downward bias of the gap at the top of the distribution for both groups of workers, it does not explain the pattern found at the bottom of the distribution for the group with lower education.

[5] Indeed, a more proper name would be 'glass ceilings at the ground floor' since it refers to gender pay gap at the bottom quantiles of the wage distribution. However, we will use 'glass floors' for the sake of brevity.

(1981) predicts that women choose occupations where the cost of career interruptions is low and the fact that occupational segregation by gender segregation exists in the labor market would support this argument.[6] Another explanation relies upon the fact that women have a lower probability to be promoted to jobs with higher responsibilities even in the case where they have both the same ability distribution than men. The model by Lazear and Rosen (1990) confers a higher productivity in the household to women, an assumption that makes employers reluctant to invest in their training on an equal basis with men. Only the more productive women would be promoted.

In either group, the gender gap displayed in the previous graphs could be attributed to a *lower productivity* of women or to a *lower market return* for a given characteristics, usually related to the discrimination component or to unobserved variables. In order to disentangle these components we follow the conventional decomposition procedure, albeit adapted to analyzing gender gaps at the quantiles instead of at the mean wage. First, we estimate quantile regressions (QR) to obtain the return to the productive characteristics for men and women. Next, following Albrecht et al. (2003), we make use of the Machado and Mata´s (2004) adaptation of the popular Oaxaca-Blinder decomposition to a QR framework in order to isolate the two effects at work.[7]. Our main finding when applying this technique is that different characteristics only account for one-fourth of the raw gender gaps and that the unexplained components very much presents the same increasing/decreasing patterns displayed in Figures 1b and 1c. Furthermore, we find that the differences in returns to tenure in favour of women are much higher at the bottom of the wage distribution when we consider the L-group, yet the differences are negligible in the case of the H-group. Since age and tenure and age increase over the distribution (see section 3.2 below), this could be interpreted as employers offering a higher reward to an

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[6] For a comparative study of gender occupational segregation between US and the EU, see Dolado et al. (2004).

[7] It can be argued that, given the low participation of L-type women in Spain, a sample selection bias correction á la Heckman should be used to estimate the wage equation for this group. Indeed, in a previous version of this paper (see Dolado and Llorens, 2004) we did that. We found that the gap was larger with the correction, since the expected wage for the entire population of women is smaller than the expected wage for the current female working population. Yet, the results discussed reported below in Section 5 remain qualitatively the same. Note that this correction would only be necessary if we wished to make inference about *all* women of working age (employed or not). However, such is not the case if we were just interested in examining the gender gaps for the *existing* (in 1999) populations of male and workers. Thus, the latter is the correct interpretation of the results reported in the sequel. A recent study analyzing the econometric techniques needed to account for sample selection bias corrections in quantile regressions is Albrecht et al. (2004).

extra year of tenure in the case of less-educated women with low tenure than in the case of men.

This last finding, which seemingly corroborates the statistical discrimination hypothesis, can be further explored by exploiting the panel dimension of the ECHP which allows one to get rid of the time-invariant unobserved heterogeneity that is always present in cross-sectional studies. Using the eight available waves (1994-2001) of the ECHP, we estimate (log) wages using fixed effects estimation so as to check whether the returns to tenure are higher for women than for men in the L-group. If employers suspect that the propensity to quit of L-type women is much higher than that of H-type women, longer tenure will be disproportionately rewarded vis-á-vis men for the former group.

The rest of the paper is organized as follows. In Section 2, we offer a simple theoretical model that is consistent with the glass floor pertaining to the L-group, and review the existing explanations for the glass ceiling observed for the H-group. Section 3 is devoted to describe the econometric methodology (QR), the data employed and the results of the gender regressions. In Section 4 we perform the gender gap decomposition at the mean and at the unconditional quantiles. Section 5 exploits the panel dimension of the ECHP to provide further support to the statistical discrimination hypothesis underlying the glass floor phenomenon. Finally, Section 5 concludes. An Appendix offers a detailed description of the data.

2. Interpretative models

2.1 Glass floors: L-group

To account for the stylized facts in the quantile evolution of the gender gap for the L-group, we use a simple model motivated by Acemoglu and Pischke (1998)´s analysis of the financing of training in frictional labour markets.

Let us assume that workers are endowed with an ability δ whose c.d.f., $G(\delta)$, is identical for men and women. Low-educated workers need to get specific training to perform a job so that two periods are considered. In the initial period, workers receive training so that firms bear an investment cost leading to a productivity $\gamma_1\delta$ with $0 < \gamma_1 < 1$. At this point firms do not know the worker's productivity that becomes revealed at the beginning of period 2. The training leads to a higher productivity $\gamma_2\delta$ in period 2, such that $\gamma_1 < 1 < \gamma_2$. Workers receive a disutility shock, ω, which forces them to quit the job (say, for family duties), as in Acemoglu and Pischke (1998). The ω shock is a random variable with c.d.f. $F(\omega)$ which is revealed (independently) twice to the worker: (i) after the worker is hired for the training period and once the wage in period 1, W_1, has been offered by the firm; and (ii) once they have started the second period and again after the wage in the second period, W_2, has been chosen by the firm.

Thus, workers will get trained in period 1 as long as $W_1 - \omega \geq 0$ and will work in period 2 if $W_2 - \omega \geq 0$. Moreover, to stress the monopsony argument emphasized by these authors, neither wage renegotiations nor wage offers from outside firms for job quitters are considered.

The key difference between men and women is that the c.d.f. for men, $F_m(\omega)$, is stochastically dominated by the c.d.f. for women $F_f(\omega)$, namely $F_m(\omega) > F_f(\omega)$ for $\omega > 0$. Through this assumption it is captured the fact that women have higher outside opportunities (say, at home production) than men. To simplify the algebra, and without loss of generality in terms of the qualitative results, we will assume that dG(.) and dF(.) are uniform distributions, such that the density functions $g(\delta) = U[0,\tau]$, $f_m(\omega) = U[0, \varepsilon_m]$ and $F_f(\omega) = U[0, \varepsilon_f]$, with $\varepsilon_f > \varepsilon_m$.

To solve for both wages, we proceed backwards in time. Under the assumption that the wage in period 2, W_{2i}, is offered before ω is realized, that firms know δ in that period, that no wage renegotiation is allowed, and that the worker has not quitted in period 1, they will choose W_{2i} to maximize expected profits in period 2, $\Pi_2(W_{1i})$, namely, the product of the probability of not quitting in period 1 ($F_i(W_{1i}) = W_{1i}/\varepsilon_i$) and the profit in period 2, that is

$$\max_{W_{2i}} \int_0^{W_{2i}} \frac{W_{1i}}{\varepsilon_i}(\gamma_2\delta - W_{2i})\,dF_i(\omega) = \max_{W_{2i}} \frac{W_{1i}}{\varepsilon_i}\left[\frac{\gamma_2\delta W_{2i}}{\varepsilon_i} - \frac{W_{2i}^2}{\varepsilon_i}\right], \quad i = f, m, \tag{1}$$

whereby the first-order condition w.r.t. W_{2i} implies that the same wage will be paid in equilibrium to workers of each gender with observed productivity δ, namely $W_{2m}^* = W_{2f}^* = \gamma_2\delta/2$.[8] Thus, the gender wage gap in period 2 will be zero. Notice, moreover, by replacing W_2^* in the bracketed term in (1), that the firm ´s expected profits when hiring men and women are $W_{1m}\,(\gamma_2\delta)^2/4\,\varepsilon_m^2$ and $W_{1f}\,(\gamma_2\delta)^2/4\,\varepsilon_f^2$. Thus, expected profits in period 2, $\Pi_2(W_{i1})$, are a function of the wages in period 1.

Next, having chosen W_2^*, under a free entry assumption, firms choose the training wages in period 1, W_{1i}^*, so as to maximize overall expected profits when hiring, that is

$$\max_{W_{1i}} \left\{\int_0^{\tau} \Pi_2(W_{i1})\,dG(\delta) + \int_0^{\tau}\left[\int_0^{W_{1i}} (\gamma_1\delta - W_{1i})\,dF_i(\omega)\right]dG(\delta)\right\}, \tag{2}$$

where, since the bracketed integral is $(\gamma_1\delta\, W_{1i} - W_{1i}^2)/\varepsilon_i$, the f.o.c. of (2) yields

[8] This is just the average of the worker s productivity´ and the outside wage which is assumed to be zero. The weight ½ in the average is due to the choice of the uniform distribution in the illustration. Alternative distributions will give rise to a weighted average with unequal weights.

$$W_{1i}^* = \frac{\gamma_1 \tau}{4} + \frac{\gamma_2^2 \tau^2}{24\varepsilon_i}. \quad (3)$$

Given the higher quitting probability of women, the gender wage gap in period 1 will be $W_{1m}^* - W_{1f}^* = \frac{\gamma_2^2 \tau^2}{24\varepsilon_m \varepsilon_f}\left[\varepsilon_f - \varepsilon_m\right] > 0$. Insofar as $W_{2i}^* > W_{1i}^*$, which occurs when $\gamma_2 \delta > \frac{\gamma_1 \tau}{2} + \frac{\gamma_2^2}{12\varepsilon_i}\tau^2$, the previous result implies that the gender gap will be larger at the bottom of the distribution (wages in period 1) than at the top if the distribution (wages in period 2).[9]

The intuition for this result is quite simple. Since the disutility shock is not known at the time when W_2 is offered, the best that firms can do is to match this outside offer by setting a wage equal to a fraction of the observed productivity $\gamma_2\delta$ which, under a uniform distribution, equals $\gamma_2\delta/2$. Hence, firms will obtain a surplus of $\gamma_2\delta$ - $W_2^*= \gamma_2\delta/2$ in period 2 and, given the f.o.c. in period 1, they have to pay a wage above $\gamma_1\tau/4$ (i.e., the expected wage conditional on staying) in that period. Since expected profits in period 2 are higher with more stable male workers than with less stable female workers (because $W_{1m}^* (\gamma_2\delta)^2 / 4\ \varepsilon_m^2 > W_{1f}^* (\gamma_2\delta)^2 / 4\ \varepsilon_f^2$) firms will pay a higher wage to men than to women in period 1. This explains both why the wage profile is flatter than the productivity profile and why women receive a lower wage in period 1 (the lower part of the distribution) than men.

2.2 Glass ceilings: H-group

As for the presence of the conventional glass ceiling phenomenon in the H-group, we mentioned in the Introduction several rationalizations available in the literature. Amongst the most popular, there is the one provided by Lazear and Rosen (1990) in a model of job ladders. In their model firms have to choose how to place workers, namely either in a flat ladder (A, with no training), where productivity in both periods is δ or in a promotion ladder (B, with training) where productivities are $\gamma_1\delta$ and $\gamma_2\delta$ in periods 1 and 2, respectively, with the rest of the assumptions given above except that firms are competitive and pay wages in period 2 equal to observed productivities, i.e., $W_2^A= \delta$ and $W_2^B= \gamma_2\delta$. Given women's larger propensity to quit in period 2, firms choose a more

[9] Averaging over productivity, the previous inequality holds for sufficiently high values of ε_f and ε_m. Note that, although the results of the model could be more naturally interpreted as explaining gender gaps by age or tenure (since there are two periods) rather than by location in the wage distribution, age and tenure increase monotonically along the distribution (see Table 1c in section 3.2).

stringent cutoff ability to allocate them to the B job than the one chosen for men. Thus, denoting each cutoff by δ_f*and δ_m*, respectively, we have that $\delta_f^* > \delta_m^*$. This result implies that there are women with δ such that $\delta_m^* < \delta < \delta_f^*$ who are not promoted. In other words, to be promoted, a woman must be more productive than a man to compensate for her ex ante probability of departure and the loss of the training investment. The prediction from the model about the difficulties faced by women in climbing the job ladder is well supported by the empirical evidence.[10] However, in a competitive market, the other key prediction - namely that if men and women have the same underlying ability distribution, then the average wage of females in A jobs should be larger than the average wage of men in that job- is at odds with the available evidence (i.e., the glass ceiling phenomenon). As Lazear and Rosen (1990) note, one way to solve this puzzle is to apply Mincer and Polacheck's (1974) argument suggesting that different expectations by men and women of labour market participation would result in different ability distributions since women would self-select to relatively low-paid occupations where career interruptions are less penalized. Alternatively, Booth et al. (2003) depart from the assumption of perfect competition by introducing some monopsonistic power by firms. They assume that women in highly-paid jobs receive a smaller number of outside offers (due to their 'perceived' lower mobility) that the firm might be interested to match in order to retain the worker. Likewise, other explanations rely upon women having less bargaining power than men in labour markets where there are rents to be shared with firms[11]. In either case, the implication of all these models is that women in good jobs will be lower paid than men in those jobs.

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[10] For example, Bertrand and Hallock (2001), who analyze the group of high-level executives in US corporations, find that women only represent 2.5 % of the sample, and show that the main reason behind their lower earnings is that they lead smaller firms, are younger and have less tenure. Of course, these findings do not rule out the existence of discrimination in terms of gender segregation or promotion.

[11] In a experimental framework, Gneezy et al. (2003) notice that men and women have different attitudes to competing. Men try harder to compete and therefore disproportionately win the top jobs, even when to do the job well does not require an ability to compete. In a similar vein, Babcock and Laschever (2003) notice that male graduates with a master's degree at Carnegie Mellon University earned starting salaries 7.6% higher than female students, because the latter tend to accept the initial pay offer much more frequently than their male classmates. Sociological explanations based on women wanting opportunities but not a life dominated by work may be behind these attitudes.

3. Methodology, Data and Results

3.1 Methodology (QR)

Following Koenker and Bassett (1978) and Buchinsky (1998), the model of QR in a (log) wage-equation setting can be described as follows. Let (w_i, x_i) be a random sample, where w_i denotes the (logged) hourly gross wage of an individual i and x_i is a vector K ×1 of regressors, and let $Q_\theta(w_i | x_i)$ be θth-order quantile of the conditional distribution of w_i given x_i. Then, under the assumption of a linear specification, the model can be defined as[12]

$$w_i = x_i'\beta_\theta + u_{\theta i} \qquad\qquad Q_\theta(w_i | x_i) = x_i'\beta_\theta \tag{4}$$

where the distribution of the error term $u_{\theta i}$, $Fu_\theta(\cdot)$, is left unspecified, just assuming that $u_{\theta i}$ satisfies $Q_\theta(u_{\theta i} | x_i) = 0$. The estimated vector of QR coefficients, $\hat{\beta}_\theta$, is interpreted as the marginal change in the conditional quantile θ due to a marginal change in the corresponding element of the vector of coefficients on x, and can be obtained using the optimization techniques described in Koenker and Bassett (1982).[13]

3.2 Data and Results

The data are drawn from the 1999 (6th. wave) of the ECHP which provides information in a harmonized format for the EU countries on earnings, employment, hours of work, education, immigrant condition, civil and health status and other socio-demographic variables. The information is obtained from surveys to a fixed panel of households (70,000 in the EU and around 8,000 in Spain) since 1994. Our sample is restricted to full-time workers working more than 15 hours per week and, as discussed earlier, we distinguish between two groups by educational attainments. In the H-group there are 721 men and 558 women whereas the L-group is formed by 1,585 men and 626 women. Appendix A contains a detailed description of the variables used in the regression models while Tables 1a and 1b offer summary descriptive statistics of both samples.[14] As can be observed, the mean gender gaps are around 10% and 23% for the H and L-

[12] If the linear specification were not to be correct, we can always interpret model (4) as the best linear predictor for the conditional quantile.

[13] Although $\hat{\beta}_\theta$ is a consistent estimator for β_θ and asymptotically normal, it is not efficient. An efficient estimator requires the use of an estimator for the unknown density function $f_{u\theta}(0 | x)$.

[14] Descriptive statistics of women in the L-group who do not work are also reported since they are used to run a probit on participation.

groups, respectively.[15] H-type men have more (potential) experience than H-type women (2.1 years), have longer tenure (0.6 years), are a bit older (1.8 years) and have a larger share in directives jobs (a 10 p.p. difference).[16] By contrast, L-type men are much more experienced than women (4 years) yet, as before, they have a longer tenure (0.85 years) and are older (1.7 years). In both groups women have a larger share in firms with less than 20 employees and work more often in the public sector. Finally, Table 1c presents the evolution of experience and tenure throughout the main quantiles, confirming that both increase monotonically as we move up the distribution. Typically, when comparing the 10th and 90th quantiles for the H (L) group, age and tenure increase by 30 and 20 years (35 and 20 years), respectively.

[Tables 1a, 1b and 1c about here]

We have estimated QR equations (reported at the 10th, 25th, 50th, 75th and 90th quantiles) where the (logged) gross hourly wage is regressed on different subsets of covariates. Heteroskedastic-robust estimation at the conditional mean has also been undertaken for comparison purposes. As is conventional in *mincerian* wage equations, the controls in each of the two educational groups are: potential experience/age and its square, experience interacted with age of children,[17] tenure in the current job, marital status, age of children and secondary education (only for the L-group). To consider the demand side of the labour market, regional dummies and size of local council have also been included. We control as well for firm size, immigrant condition, type of contract (permanent or temporary), sector (private or public) and supervisory role. Further, we added 15 occupational dummies which are arguably endogenous, yet they are useful in explaining the gender gap from an "accounting exercise" point of view.[18]

We start the analysis by running a pooled OLS regression, both at the mean and at the above-mentioned quantiles, for men and women in the H and L-groups, respectively, where a (female) gender dummy captures the extent to which the gap remains unexplained after controlling for individual differences in

[15] Note that the compared percentiles correspond to the wage distributions of men and women separately. If we were to consider the position of women in the men's distribution, it is found that 13.6% (3.8%) of women are in the bottom (top) percentile of the distribution for the H-group, while 31% (5.4%) of women are in those percentiles for the L-group.

[16] Actual work experience is unavailable in the ECHP and therefore only potential experience (age-years of education-6) can be used. Since we split the sample by education, this variable is very much like age. Thus, we exclude age in the regressions and interpret the estimated coefficient on the variable labeled (potential) *Experience* as the return on age.

[17] This interaction term aims at capturing the effect of child care on experience.

[18] Unfortunately, the ECHP does not provide information on parents' education or occupation, which could provide appropriate instruments to correct for endogeneity.

the observed characteristics whose returns are restricted to be the same for both genders. Although the results of this pooled estimation are not reported to save space, the intercept for the gender dummy turned out to be always negative and significant, declining (increasing) in absolute value in the L-group (H-group) as we move up the distribution. [19] However, these results are only tentative since the null hypothesis of equal coefficients on the covariates for both genders is rejected with a p-value of 0.006.

Hence, in view of this rejection, the next step is to relax the assumption of equal returns to the observable characteristics and run separate QR equations for men and women. The results are presented in Tables 2a (males in H-group) and 2b (females in H-group), and in Tables 2c (males in L-group) and 2d (females in L-group). The following findings stand out. The coefficients on age/experience for men in the H-group are always larger than the coefficients for women and the gap grows slightly as we move up the distribution, in common with the findings of Albrecht et al. (2003). In contrast, returns to tenure appear to be very similar to both men and women at most percentiles but at the very top one, where men exhibit higher returns than women. We also find that the return from performing a supervisory role is larger for men, particularly from the 50th percentile onwards. Being married has a lower return for women particularly at the bottom of the distribution where it provides a signal to the employers of potential career interruptions. By contrast, working in a firm with more than 20 employees has a larger return for women, as is the case of working in the public sector at the 25th and 50th percentiles. The presence of strong collective bargaining and affirmative action in the public sector may be behind the latter result. As for the occupational dummies (not reported), the results point out that women in teaching jobs (OC4, OC6) get larger rewards than men and that the differential switches in favour of men at the top quantiles of most of the remaining occupations.[20]

[Tables 2a, 2b, 2c, 2d about here]

With regard to the L-group, the coefficient on age/experience for men is again larger than for women but this time with the gap decreasing as we move up the distribution. Further, having a secondary educational attainment yields a higher return for women, as is also the case of working in the public sector or having a permanent contract. Also, as before, the coefficients on being married are larger

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[19] The estimated average gaps are -7.63% and -19.67% for the H and L groups, respectively.

[20] The fact that women have larger coefficients than men in some of the occupations (relative to the reference group of unskilled workers) does not imply that they get a higher wage since they may have a lower wage in the reference category. A similar comment pertains to the coefficients on the rest of the dummy variables.

for men, particularly at the lower quantiles. The most interesting finding, however, is that the return to tenure is higher for women than for men at the lower quantiles and then both converge to the same value as we move up the distribution. This finding can be rationalized in the following way. According to the model in section 2.1, attachment of L-type women is an uncertain outcome for their employers, particularly at the early stages of their careers. Thus, the reward to longer tenure (i.e., a reduction in uncertainty) should be higher than for the "more stable" men. This explanation somewhat mimics the standard one available in the literature about statistical discrimination concerning the employer private learning process about workers´ ability. As the employer learns more about the worker, the return on education (the signal) decreases while the return on experience increases (see, e.g., Farber and Gibbons, 1996). Finally, notice that excess returns to tenure for women do not appear in the H-group since participation rates for both genders are high in this group.

In sum, the evidence presented so far points out that returns to observable characteristics differ by gender and that these differences change as we move throughout the distribution. The next step is to investigate how important is discrimination is explaining the gender gap.

4. Decomposition of the gender gaps

4.1 Methodology (MM decomposition)

A useful way of thinking about the well-known Oaxaca-Blinder decomposition is to compare actual observations with counterfactual ones. In particular, denoting women's and men's returns by β_f and β_m and their characteristics by x_f and x_m, respectively, one is interested in knowing the wage that a woman would receive if she were paid according to women's returns (β_f) but had men's characteristics (x_m). In a market without discrimination ($\beta_f = \beta_m$), men's wages would be equal to those fictitious women's wages as long as they have the same productive characteristics. Therefore, when considering counterfactual wages of women, observed wage differences between men and women can be attributed to unequal treatment by gender. It should be noted, however, that the discrimination measures based on the mean are not directly applicable to other points of the wage distribution. Indeed, while the decomposition of the mean wage gap is exact (since inclusion of a constant term in the equation ensures that the OLS residuals have zero mean), this property is lost when applied to the gender wage gap at quantile θ.

In effect, in the case of the mean, $E(w_i/x_i) = x_i'\beta$ implying that the Oaxaca-Blinder decomposition yields $E(w^m) - E(w^f) = (E(x^m) - E(x^f))'\beta^m + E(x^f)' (\beta^m - \beta^f)$.

The first term measures the differences in the mean wage due to *different endowments of characteristics*, whilst the second term captures the differences due to *different returns to these characteristics*.[21]

However, in QR, taking expectations of (4), subject to the (logged) wage being equal to its unconditional quantile of order θ, i.e., $w_i = \omega_{\theta i}$, yields

$$\omega_\theta = E(x \mid w = \omega_\theta)'\beta_\theta + E(u_\theta \mid w = \omega_\theta),$$

namely, the θ quantile of the (log) wage distribution is equal to its θ conditional quantile evaluated at the vector of mean characteristics of the individuals at that quantile, plus the mean value of the error term for this group of individuals. Thus, in contrast to the OLS decomposition at the mean, evaluation of the conditional quantile wage function at $E(x \mid w = \omega_\theta)$ does not yield the desired decomposition. For this reason, we follow Albrecht et al.'s (2003) adaptation of Machado and Mata (MM)'s (2004) bootstrap method to implement the decomposition directly at each quantile.

The steps in this procedure can be summarized as follows:

- Using a standard uniform distribution, sample a quantile, say, the θ-th quantile.
- With the male database, estimate the coefficient vector β_θ^m at the θ -th quantile.
- From the female database, take a draw from the women ´s data (x^f), and construct a predicted wage by multiplying the chosen x^f by the estimate of β_θ^m. Repeat this N times (e.g. N=100) and construct a counterfactual male distribution, namely what women would have earned if they were "paid like men".
- Then use this generated wage distribution to construct the counterfactual gap ($\beta_\theta^m x^f - \beta_\theta^f x^f$) which yields that part of the raw gap explained by different rewards, i.e., $(\beta_\theta^m - \beta_\theta^f)x^f$. [22]

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[21] In line with most of the literature, we chose to evaluate differences in observed characteristics at the men ´s returns, under the assumption that their market rewards wages are not distorted by discrimination.

[22] Notice that by implementing this decomposition, in contrast to Albrecht et al. (2003), we are evaluating the difference in characteristics, ($x^m - x^f$), at the market returns of men, β_θ^m. By interchanging the role of men and women in the MM procedure, which is what these authors do, we can obtain the alternative evaluation at women´ s rewards, β_θ^f, so that the *Returns* component

The whole procedure has been replicated 250 times in order to obtain standard deviations of the contribution of these components.

4.2 Results of the decomposition

Tables 3a and 3b present the results of the MM decomposition for the H and L-groups, respectively, whereas Figures 3a and 3b depict the raw and the generated counterfactual gaps in each of the two cases. For the H-group, Table 3a shows that the *Returns* term increases as we move up the distribution to reach about 90% of the raw gap at the 90-th quantile. This can be corroborated in Figure 3a where it becomes evident that the counterfactual gap (unexplained component) is increasing along the distribution, in line with the glass ceiling hypothesis. This can be corroborated in Figure 3a where it becomes evident that the counterfactual gap is increasing along the distribution, implying that the gender gap is mainly due to differences in observed characteristics at the bottom of the distribution, but to differences in rewards at the top of it. This evidence is very much in line with the glass ceiling hypothesis.

[Tables 3a, 3b about here]

Table 3b displays the corresponding results for the L-group. In stark contrast to the previous case, the counterfactual gap depicted in Figure 3b is now decreasing along the distribution reaching a minimum of about 50% at the 75th quantile, in accord with the glass floor hypothesis. Furthermore, contrary to the H-group, the gender wage gap is basically due to differences in returns at the bottom of the distribution and to differences in observed characteristics at the top of the distribution.

[Figures 3a, 3b about here]

5. Testing statistical discrimination with panel data

In the previous section we have advanced an explanation for the glass floors observed for the L-group based on QR under the assumption, supported by the evidence, that age and tenure increase as we move up the wage distribution. Hence, this would vaguely support the interpretation of the wages in the lower quantiles as corresponding to entry jobs or the early years in a job career. However, our conjecture could be greatly reinforced if we were to follow individuals in the *same* firm *over time*, something which naturally cannot be done using a single cross-section, as in the QR framework. To do this, we can exploit the panel dimension of the ECHP using its eight available waves (1994-2001)

becomes (β_θ^m - β_θ^f)x^m. The results of this alternative decomposition are not presented but the qualitative findings about the unexplained gaps remain the same.

rather than a single one (1999) as above. The idea is to use panel data estimation (in particular, fixed effects estimation) of similar wage equations to the ones estimated so far to test for the sign and significance of the interaction of tenure and gender (female) in each educational group. Given that L-type men have higher participation rates (and hence average tenure) than women, we should expect that an extra year in the same firm yields a higher reward for the latter so that the gender gap decreases as women do not quit. As argued above, this will not be the case in the H- group where both men´ s and women ´s participation rates are high. Therefore, we should expect a positive and significant coefficient for the interaction term *Tenure* Female* in the wage equation for the L-group and a non-significant one for the H-group. Moreover, the return to an extra year of tenure of a L-type woman is bound to increase much more when they are young, since they are likely to have or look after children (higher probability of quitting), than when they are older. For this reason, we carry out the estimation splitting the sample into two age groups, i.e., below and above 40 years of age (at the first interview), expecting to find a much larger coefficient on the interaction term for the younger group.

Table 4a presents the descriptive statistics regarding (logged) wages and tenure of the overall sample which consists of an unbalanced panel that contains 22,263 observations, out of which 15,322 belong to the L-group and 18,192 to the group below 40 years of age. The reported estimates have been obtained from fixed-effects estimation. Table 4b and 4c reports the estimated coefficient on *Tenure* (and its square) and on *Tenure* Female* for each age group, estimated separately in the H and L- samples and pooled to test for its statistical significance (last two columns of each Table) . As can be observed, the latter coefficient is only statistically significant and positive (highlighted in bold) in the equation for the younger L-group, in line with our previous conjecture on the role of statistical discrimination in explaining the glass floor phenomenon. Finally, notice that, by controlling for fixed-effects, to the extent that unobserved heterogeneity is time invariant, the alternative explanation to the glass floors based on such a heterogeneity affecting the L-type women via-á-vis men gets weakened.

6. Conclusions

In this paper, we have analyzed the evolution of gender gaps along the wage distribution in Spain using the 1999 (6th wave) of the ECHP under a QR framework. Our main finding is that, behind an irregular and somewhat flat evolution for the whole sample of individuals, there is distinctive difference between the patterns of the gender gaps when we distinguish by educational attainments (individuals with primary/secondary education, L-group, and with tertiary education, H-group). While for the H-group the gender gap is increasing along the distribution, it happens to be decreasing for the L-group. Further, using Machado and Mata (2004) ´s adaptation of the Oaxaca-Blinder decomposition to QR, these patterns remain when we control for the different observable characteristics which men and women bring to the labour market. Further, while this evolution contrasts with that found for northern and central European countries, where the gender gap is increasing as we move up the distribution irrespectively of educational attainments, it seems to be similar to that found for other southern European countries, like Italy, where female labour market participation of L-type women is still rather low.

Our explanation for these divergent patterns is as follows. Due to the historical low participation of women in the L-group, employers may use statistical discrimination to lower their wages vis-à-vis more stable men in the lower part of the wage distribution since they expect future career interruptions to jeopardize their financing of specific training. However, as their job tenure expands, women become more reliable to employers' eyes and their wages converge to men's wages with the same characteristics. By contrast, women in the H-group, who have undergone a costly investment in human capital, can be expected to be more stable, since their participation rate is much larger, and therefore are less discriminated at the bottom on the wage distribution. However, for reasons related to their lower job mobility or bargaining power, they suffer from larger gaps at the top of the distribution. Hence, there seems to be a "composition effect" in the overall gender gap, when both groups are lumped together: while there is a *glass floor* the L-group, there is a *glass ceiling* for the H-group.

The statistical discrimination hypothesis for the L-group is reinforced when we exploit the panel dimension of the ECHP following the gender gaps as women stay longer in the same firms. The market return to longer tenure is larger for younger (below 40) L- type women than for their male counterparts, leading to lower gaps as their tenures expand. This finding, however, does not hold either for H-type workers or for older workers.

There are three topics for a future research agenda. First, we wish to explore how statistical discrimination has evolved over time as there is some evidence that the traditional patterns of quit rates by gender may be changing in unexpected ways.[23] Second, a more general approach to perform the MM decomposition would be to derive a non-discriminatory wage structure from a theoretical model that is neither completely masculine nor feminine (see Neumark, 1988). Several studies show that conclusions on the source of the

[23] For instance, there is evidence for the late 1990s that the number of women working in managerial positions who take maternity leaves is three times smaller that the number of men in similar positions taking leaves for stress (see Chinchilla, 2003).

gender gap hinge crucially on different assumptions on the nature of the non-discriminatory structure. Finally, we would like would be to extend the analysis to other EU countries with low participation rates (e.g. Greece or Italy) taking advantage of the data harmonization provided by the ECHP.

Appendix

A.1: Definition of variables

The variables are drawn from the 1999 (6^{th} wave) of the ECHP. Our group of interest is composed by wage earners working full-time and more than 15 hours per week. In this section we include a detailed description of the variables used in the analysis.

Gross hourly wage: The ECHP collects data on average monthly labor income (gross and net), from salaried workers. Labor income includes salary bonus (divided by working months), and overtime. When a worker has more than one job, only the main job income is considered. Weekly hours in the main job are available, including overtime hours. We have set an upper bound of 60 hours to this variable in order to minimize the self-declared bias. This correction affects 2% of men and 0.9% of women from our total sample. Then, gross hourly wage is the monthly gross salary divided by 52/12 and multiplied by the weekly hours worked in the main job.

Experience: defined as age minus years of schooling (8 for primary education, 12 for secondary and 15 for tertiary in Spain) minus 6.

Exp*Children: interaction between experience and a binary variable that takes a value of 1 when an individual has dependent children (from 0 to 16 years). In the basic set of covariates, we consider separately the case in which children are between 0 and 11 years (Exp*Children 0-11) or between 12 and 16 years (Exp*Children 12-16).

Level of education: primary or secondary. This dummy variable is only included for the L-group.

Individual characteristics: marital status, immigrant condition, district of residence and district size.

Type of contract: temporary or permanent.

Sector: private or public.

Supervisory role: directive or managing position, supervisor of at least another employee and without responsibility for the rest of employees.

Tenure: obtained as the difference between the year of the survey, 1999, and the year of the start of the current job.

Firm size: from 1 to 4 employees, from 5 to 19 employees, from 20 to 49 employees, from 50 to 99 employees, from 100 to 499 employees and above 500 employees.28

Occupation: fifteen occupational groups have been considered, corresponding to an intermediate level of aggregation of the ISCO-88 (COM) classification. We have distinguished among: Legislators, senior officials and managers (OC1); Physical, mathematical, engineering, life science and health professionals (OC2); Teaching professionals (OC3); Other professionals (OC4); Physical, mathematical, engineering, life science and health associate professionals (OC5); Teaching and other associate professionals (OC6); Clerks (OC7), Models, salespersons and demonstrators (OC8); Personal and protective services workers (OC9); Skilled agricultural and fishery workers (OC10); Extraction and building trades workers, other craft and related trades workers (OC11); Metal, machinery, precision, handicraft printing and related trades workers (OC12); Plant and machinery operators and assemblers (OC13); Sales and services elementary occupations (OC14); and Agricultural, fishery and related laborers, laborers in mining, construction, manufacturing and transport (OC15).

Table A1: Labour activity rates by educational attainment (2002)

Countries	**Men**			**Women**		
	Less than secondary	*Secondary*	*Tertiary*	*Less than secondary*	*Secondary*	*Tertiary*
Denmark	75.4	87.3	92.7	55.8	80.7	88.4
Sweden	78.0	87.9	90.4	65.1	83.4	88.1
United Kingdom	65.9	88.1	92.2	50.7	76.4	87.3
Spain	83.5	90.1	91.9	42.3	67.6	83.1
Italy	75.5	86.1	90.9	34.8	67.9	82.7
Greece	81.0	88.5	89.7	42.1	57.2	82.4

Source: OECD, Employment Outlook, 2002

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Table 1a. Descriptive statistics. H-group; Spain (1999)

	Men		Women	
	Average	*St. dev*	*Average*	*St. dev*
N. observations	721		558	
Age	37.61	10.34	35.78	9.49
Children 0-11	0.44	0.77	0.28	0.45
Children 12-16	0.22	0.50	0.13	0.33
Age Groups				
17 to 24	0.07	0.26	0.09	0.28
25 to 34	0.37	0.48	0.45	0.50
35 to 44	0.31	0.46	0.28	0.45
≥ 45	0.25	0.43	0.19	0.39
Married	0.62	0.49	0.55	0.50
Immigrant	0.003	0.05	0.01	0.07
Weekly hours	41.22	6.54	38.31	5.94
Ln (gross hourly wage)	7.28	0.55	7.18	0.50
Experience	14.78	10.40	12.68	9.71
Occupation				
OC1	0.05	0.23	0.02	0.13
OC2	0.14	0.35	0.16	0.36
OC3	0.11	0.32	0.25	0.43
OC4	0.09	0.28	0.09	0.29
OC5	0.09	0.29	0.05	0.22
OC6	0.09	0.28	0.13	0.34
OC7	0.10	0.29	0.19	0.39
OC8	0.05	0.21	0.05	0.22
OC9	0.02	0.15	0.03	0.18
OC10	0.01	0.07	0.00	0.00
OC11	0.07	0.25	0.00	0.04
OC12	0.08	0.27	0.00	0.04
OC13	0.07	0.25	0.01	0.12
OC14	0.02	0.13	0.01	0.11
OC15	0.02	0.12	0.01	0.08
Firm Size				
1-4 employees	0.07	0.26	0.10	0.31
5-19 employees	0.21	0.41	0.22	0.41
20-49 employees	0.17	0.38	0.21	0.40
50-99 employees	0.13	0.33	0.10	0.30
100-499 employees	0.18	0.39	0.14	0.35
> 500 employees	0.24	0.43	0.23	0.42
Public sector	0.35	0.48	0.51	0.50
Supervisory role				
Directive	0.16	0.37	0.06	0.24
Supervisor	0.27	0.45	0.25	0.43
W/o responsibility	0.56	0.50	0.69	0.46
Tenure	8.32	7.61	7.65	7.35
Permanent contract	0.80	0.40	0.73	0.44

Table 1b
Descriptive statistics
L group; Spain
(1999)

	Men		Women	
	Average	*St. dev*	*Average*	*St. dev*
N. observations	1585		626	
Age	37.89	11.31	36.19	11.33
Children 0-11	0.30	0.46	0.21	0.41
Children 12-16	0.16	0.37	0.17	0.38
Age Groups				
17 to 24	0.13	0.33	0.18	0.38
25 to 34	0.31	0.46	0.32	0.47
35 to 44	0.25	0.43	0.23	0.42
≥ 45	0.31	0.46	0.27	0.45
Married	0.68	0.47	0.53	0.50
Immigrant	0.004	0.07	0.01	0.08
Secondary ed.	0.29	0.46	0.38	0.49
Weekly hours	42.64	6.19	40.36	5.74
Ln (gross hourly wage)	6.86	0.41	6.63	0.47
Experience	20.77	12.41	16.78	11.85
Occupation				
OC1	0.02	0.14	0.01	0.11
OC2	0.00	0.00	0.00	0.00
OC3	0.00	0.03	0.00	0.04
OC4	0.00	0.06	0.00	0.07
OC5	0.02	0.13	0.02	0.14
OC6	0.05	0.21	0.06	0.24
OC7	0.07	0.25	0.18	0.38
OC8	0.08	0.28	0.18	0.38
OC9	0.04	0.20	0.13	0.33
OC10	0.02	0.15	0.01	0.10
OC11	0.22	0.42	0.08	0.27
OC12	0.10	0.30	0.01	0.10
OC13	0.20	0.40	0.06	0.24
OC14	0.05	0.21	0.20	0.40
OC15	0.13	0.33	0.06	0.24
Firm Size				
1-4 employees	0.18	0.38	0.22	0.42
5-19 employees	0.31	0.46	0.25	0.44
20-49 employees	0.16	0.37	0.16	0.37
50-99 employees	0.10	0.30	0.11	0.31
100-499 employees	0.12	0.33	0.14	0.35
> 500 employees	0.12	0.33	0.11	0.32
Public sector	0.13	0.34	0.18	0.38
Supervisory role				
Directive	0.05	0.23	0.03	0.16
Supervisor	0.16	0.36	0.08	0.28
W/o responsibility	0.79	0.41	0.89	0.31
Tenure	7.27	7.75	6.41	7.28
Permanent contract	0.64	0.48	0.60	0.49

Table 1c. Experience and Tenure throughout the Wage Distribution (Spain,1999)

	Average	θ=10	θ=25	θ=50	θ=75	θ=90
MEN (H)						
Experience	14.7	2.1	6.3	13.4	22.2	29.3
Tenure	8.3	0.4	1.2	6.2	16.0	20.4
WOMEN (H)						
Experience	12.7	2.0	5.1	10.2	19.1	27.3
Tenure	7.6	0.6	1.2	5.0	14.2	20.1
MEN (L)						
Experience	21.1	5.2	11.3	20.2	31.1	38.2
Tenure	7.3	0.5	1.2	3.4	15.0	20.3
WOMEN (L)						
Experience	16.9	2.2	7.2	15.3	26.2	34.3
Tenure	6.4	0.2	0.8	3.0	11.2	19.8

Table 2a. OLS and QR
H-group (Spain, 1999)
Dependent variable : Ln. gross hourly wage

MEN	**Average**	**θ=10**	**θ=25**	**θ=50**	**θ=75**	**θ=90**
Experience	0.020***	0.012	0.016**	0.017**	0.021	0.032***
	(0.006)	(0.008)	(0.007)	(0.007)	(0.009)	(0.010)
Experience^2	-0.0003*	-0.0002	-0.0002	-0.0002	-0.00002	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Exp*Children	0.0025	0.0035	0.0033	0.0027	0.0024	0.0009
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Immigrant	-0.080	-0.007	-0.139	0.056	-0.160	-0.205
	(0.183)	(0.334)	(0.269)	(0.189)	(0.195)	(0.207)
Public sector	0.085**	0.080	0.094*	0.068	0.070	0.109**
	(0.034)	(0.070)	(0.051)	(0.050)	(0.052)	(0.055)
Permanent contract	0.074*	0.131**	0.141***	0.081	0.034	0.109*
	(0.039)	(0.058)	(0.053)	(0.049)	(0.056)	(0.062)
Supervisory role						
Directive	0.320***	0.164*	0.252***	0.298***	0.388***	0.510***
	(0.051)	(0.085)	(0.072)	(0.066)	(0.095)	(0.091)
Supervisor	0.090***	0.005	0.066*	0.107***	0.123***	0.148***
	(0.030)	(0.046)	(0.039)	(0.038)	(0.045)	(0.054)
Tenure	0.016***	0.022***	0.020***	0.017**	0.012	0.011
	(0.004)	(0.006)	(0.006)	(0.007)	(0.009)	(0.011)
Married	0.071*	0.118**	0.030	0.032	0.070	0.049
	(0.039)	(0.056)	(0.049)	(0.045)	(0.061)	(0.072)
Firm size						
5-19 employees	-0.090	0.005	-0.067	-0.087	-0.153	-0.210
	(0.067)	(0.114)	(0.073)	(0.082)	(0.111)	(0.136)
20-49 employees	-0.044	0.076	0.042	0.020	-0.096	-0.232**
	(0.065)	(0.116)	(0.085)	(0.077)	(0.094)	(0.113)
50-99 employees	0.043	0.191	0.124	0.060	-0.031	-0.206*
	(0.065)	(0.124)	(0.086)	(0.083)	(0.105)	(0.124)
100-499 employees	0.088	0.217*	0.165**	0.106	0.009	-0.112
	(0.066)	(0.121)	(0.073)	(0.080)	(0.099)	(0.113)
> 500 employees	0.144**	0.233*	0.216***	0.154*	0.094	-0.008
	(0.065)	(0.125)	(0.081)	(0.080)	(0.096)	(0.119)
Nº Obs.	721	721	721	721	721	721
R^2	0.655	0.402	0.438	0.453	0.449	0.472

Note: ***, **, * represent significance at 99, 95 and 90% respectively. Standard deviations in parentheses. Dummy variables for region, local council size and occupation are also included. Omitted group: wage earners in private sector in less-than-5-employees firms, without responsibility, single, and in non-qualified jobs in services and commerce (OC14)

Table 2b. OLS and QR

H-group (Spain, 1999)

Dependent variable : Ln. gross hourly wage

WOMEN	**Average**	**θ=10**	**θ=25**	**θ=50**	**θ=75**	**θ=90**
Experience	0.011*	0.002	0.004	0.004	0.019*	0.016
	(0.006)	(0.010)	(0.008)	(0.008)	(0.011)	(0.013)
Experience^2	-0.0001	0.00005	-0.00003	0.000004	-0.0002	-0.0002
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Exp*Children	0.0005	0.0020	0.0042**	-0.0009	-0.0004	-0.0007
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Immigrant	0.008	0.230*	0.089	0.035	0.258	0.024
	(0.128)	(0.128)	(0.143)	(0.224)	(0.311)	(0.331)
Public sector	0.097***	0.097	0.148***	0.100**	0.070	0.103*
	(0.035)	(0.061)	(0.049)	(0.044)	(0.048)	(0.061)
Permanent contract	0.119***	0.074	0.139***	0.155***	0.127*	0.069
	(0.040)	(0.068)	(0.049)	(0.048)	(0.070)	(0.082)
Supervisory role						
Directive	0.134**	0.184	0.226**	0.172**	0.138	0.074
	(0.063)	(0.149)	(0.105)	(0.076)	(0.110)	(0.130)
Supervisor	0.049	0.067	0.037	0.036	0.082	0.034
	(0.033)	(0.059)	(0.055)	(0.049)	(0.054)	(0.073)
Tenure	0.017***	0.020***	0.021**	0.017*	0.013	0.007
	(0.003)	(0.006)	(0.008)	(0.011)	(0.010)	(0.012)
Married	0.038	0.008	-0.033	0.046	0.096**	0.044
	(0.030)	(0.053)	(0.041)	(0.040)	(0.042)	(0.048)
Firm size						
5-19 employees	0.172***	0.215*	0.162**	0.187***	0.081	0.076
	(0.063)	(0.125)	(0.065)	(0.065)	(0.093)	(0.095)
20-49 employees	0.275***	0.412***	0.305***	0.286***	0.168*	0.191*
	(0.063)	(0.137)	(0.078)	(0.081)	(0.096)	(0.103)
50-99 employees	0.286***	0.399**	0.283***	0.364***	0.174	0.225**
	(0.072)	(0.169)	(0.104)	(0.090)	(0.109)	(0.110)
100-499 employees	0.364***	0.498***	0.382***	0.374***	0.305***	0.301***
	(0.064)	(0.113)	(0.076)	(0.084)	(0.092)	(0.094)
> 500 employees	0.316***	0.512***	0.338***	0.349***	0.186**	0.259***
	(0.064)	(0.113)	(0.077)	(0.086)	(0.097)	(0.097)
Nº Obs.	558	558	558	558	558	558
R^2	0.655	0.465	0.477	0.472	0.423	0.388

Note: ***, **, * represent significance at 99, 95 and 90% respectively. Standard deviations in parentheses. Dummy variables for region, local council size and occupations are also included. Omitted group: wage earners in private sector in less-than-5-employees firms, without responsibility, single, and in non-qualified jobs in services and commerce (OC14).

Table 2c. OLS and QR

L-group (Spain, 1999)

Dependent variable : Ln. gross hourly wage

MEN	**Average**	**θ=10**	**θ=25**	**θ=50**	**θ=75**	**θ=90**
Experience	0.013***	0.017***	0.010***	0.010***	0.008*	0.008
	(0.003)	(0.006)	(0.003)	(0.003)	(0.004)	(0.005)
Experience^2	-0.0002***	-0.0003**	-0.0002***	-0.0002***	-0.0001	-0.0001
	(0.00005)	(0.0001)	(0.00007)	(0.00007)	(0.00009)	(0.0001)
Exp*Children	-0.002**	-0.003*	-0.002	-0.001	-0.001	-0.001
	(0.0008)	(0.001)	(0.001)	(0.0009)	(0.0009)	(0.001)
Secondary ed.	0.060***	0.081**	0.060**	0.055***	0.025	0.023
	(0.020)	(0.040)	(0.027)	(0.019)	(0.024)	(0.035)
Immigrant	-0.143	-0.192	-0.222	-0.244	0.005	0.151
	(0.144)	(0.130)	(0.150)	(0.165)	(0.270)	(0.265)
Public sector	0.020	0.006	0.033	0.032	0.036	0.054
	(0.030)	(0.049)	(0.038)	(0.027)	(0.040)	(0.047)
Permanent contract	0.065***	0.105**	0.061**	0.028	0.037	0.073**
	(0.022)	(0.048)	(0.030)	(0.026)	(0.027)	(0.037)
Supervisory role						
Directive	0.161***	0.193***	0.113**	0.166***	0.135**	0.104*
	(0.040)	(0.073)	(0.051)	(0.050)	(0.068)	(0.059)
Supervisor	0.089***	0.083**	0.080***	0.096***	0.092***	0.074**
	(0.023)	(0.035)	(0.028)	(0.031)	(0.032)	(0.035)
Tenure	0.012***	0.015***	0.014***	0.012**	0.009*	0.010*
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)
Married	0.079***	0.123***	0.083***	0.070***	0.073**	0.077**
	(0.021)	(0.038)	(0.025)	(0.027)	(0.030)	(0.033)
Firm size						
5-19 employees	0.081***	0.132***	0.078**	0.089***	0.067*	0.082*
	(0.024)	(0.051)	(0.032)	(0.028)	(0.035)	(0.048)
20-49 employees	0.119***	0.104*	0.151***	0.125***	0.102***	0.098**
	(0.026)	(0.060)	(0.038)	(0.032)	(0.034)	(0.045)
50-99 employees	0.110***	0.106	0.147***	0.118***	0.115**	0.079
	(0.033)	(0.067)	(0.047)	(0.033)	(0.046)	(0.051)
100-499 employees	0.239***	0.231***	0.224***	0.248***	0.262***	0.274***
	(0.030)	(0.063)	(0.042)	(0.034)	(0.043)	(0.058)
> 500 employees	0.311***	0.375***	0.283***	0.340***	0.338***	0.344***
	(0.034)	(0.064)	(0.038)	(0.041)	(0.042)	(0.056)
Nº Obs.	1585	1585	1585	1585	1585	1585
R^2	0.303	0.237	0.250	0.282	0.327	0.350

Note: ***, **, * represent significance at 99, 95 and 90% respectively. Standard deviations in parentheses. Dummy variables for region, local council size and occupation are also included. Omitted group: wage earners in private sector in less-than-5-employees firms, without responsibility, single, with primary education and in non-qualified jobs in services and commerce (OC14)

Table 2d. OLS and QR
L-group (Spain, 1999)
Dependent variable : Ln. gross hourly wage

WOMEN	**Average**	**θ=10**	**θ=25**	**θ=50**	**θ=75**	**θ=90**
Experience	0.007*	0.008	0.009	0.008	0.006	0.006
	(0.004)	(0.010)	(0.006)	(0.005)	(0.006)	(0.007)
$Experience^2$	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.00009)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Exp*Children	-0.002	0.00004	-0.004**	-0.003*	0.002	0.002
	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Secondary ed.	0.113***	0.103*	0.077*	0.069	0.096**	0.155
	(0.033)	(0.059)	(0.043)	(0.043)	(0.041)	(0.060)
Immigrant	-0.479***	-0.249*	-0.358***	-0.528***	-0.584***	-0.868
	(0.073)	(0.140)	(0.112)	(0.148)	(0.144)	(0.173)
Public sector	0.108***	0.150**	0.134**	0.066	0.067	0.066
	(0.039)	(0.073)	(0.066)	(0.051)	(0.060)	(0.072)
Permanent contract	0.121***	0.194***	0.160***	0.111**	0.029	0.120
	(0.035)	(0.062)	(0.060)	(0.048)	(0.041)	(0.051)
Supervisory role						
Directive	-0.050	0.018	0.017	-0.150	0.079	0.060
	(0.129)	(0.210)	(0.138)	(0.127)	(0.184)	(0.176)
Supervisor	0.075*	0.081	0.094	0.096**	0.070	0.067
	(0.045)	(0.088)	(0.061)	(0.049)	(0.066)	(0.078)
Tenure	0.021***	0.027***	0.024***	0.016***	0.013**	0.010
	(0.004)	(0..005)	(0.006)	(0.006)	(0.007)	(0.010)
Married	0.065**	0.040	0.071*	0.093***	0.022	0.086
	(0.027)	(0.050)	(0.043)	(0.032)	(0.033)	(0.044)
Firm size						
5-19 employees	0.122***	0.137*	0.162***	0.145***	0.097*	0.063
	(0.040)	(0.074)	(0.062)	(0.056)	(0.056)	(0.060)
20-49 employees	0.255***	0.360***	0.270***	0.258***	0.177**	0.142
	(0.044)	(0.086)	(0.062)	(0.058)	(0.069)	(0.070)
50-99 employees	0.211***	0.286***	0.254***	0.191***	0.134*	0.034
	(0.053)	(0.076)	(0.069)	(0.066)	(0.073)	(0.087)
100-499 employees	0.266***	0.313***	0.293***	0.290***	0.213***	0.182
	(0.048)	(0.076)	(0.068)	(0.058)	(0.057)	(0.066)
> 500 employees	0.324***	0.281***	0.329***	0.392***	0.347***	0.194
	(0.060)	(0.092)	(0.082)	(0.075)	(0.076)	(0.082)
Nº Obs.	626	626	626	626	626	626
R^2	0.308	0.372	0.372	0.385	0.421	0.462

Note: ***, **, * represent significance at 99, 95 and 90% respectively. Standard deviations in parentheses. Dummy variables for region and local council size included. Omitted group: wage earners in private sector in less-than-5-employees firms, without responsibility, single, with primary education and in non-qualified jobs in services and commerce (OC14)

Table 3a. Counterfactual gender gaps
H-group (Spain, 1999)

	OLS	θ=10	θ=25	θ=50	θ=75	θ=90
Observed Gap	**9.74**	**8.00**	**10.20**	**10.54**	**16.68**	**24.25**
Counterfactual gap	**7.23**	**-2.38**	**1.25**	**7.37**	**15.03**	**22.28**
	(0.02)	(0.36)	(0.78)	(1.56)	(2.21)	(3.03)
%	74.2	---	12.2	79.9	90.1	92.2

Note: Standard deviations (s.d.) in parenthesis. The s.d. have been obtained through 250 replications of the decomposition

Table 3b. Counterfactual gender gaps
L-group (Spain, 1999)

	OLS	θ=10	θ=25	θ=50	θ=75	θ=90
Observed Gap	**22.73**	**33.33**	**24.71**	**17.31**	**16.82**	**18.94**
Counterfactual gap	**17.08**	**31.34**	**21.54**	**11.18**	**8.76**	**9.28**
	(0.02)	(2.27)	(1.61)	(1.52)	(1.56)	(3.26)
%	75.1	94.0	87.2	64.6	52.1	49.0

Note: Standard deviations (s.d.) in parenthesis. The s.d. have been obtained through 250 replications of the decomposition; (a) with selection bias correction.

Table 4a: Descriptive statistics of (log) Real Wages and Tenure (in years); ECHP (1994-01)								
	Workers younger than 40 at first interview				*Workers older than 39 at first interview*			
	Men		**Women**		**Men**		**Women**	
	L	*H*	*L*	*H*	*L*	*H*	*L*	*H*
Mean Log Wage	1.71 (0.37)	2.10 (0.46)	1.54 (0.34)	2.05 (0.46)	1.81 (0.38)	2.54 (0.49)	1.62 (0.43)	2.34 (0.37)
Mean Tenure	4.02 (4.72)	5.41 (5.00)	3.68 (4.35)	5.14 (4.83)	5.57 (5.67)	9.05 (5.95)	6.24 (5.40)	9.21 (5.97)
N. obs.	8617	3323	3381	2871	2394	498	930	249

Note: All workers with more than 15 years of tenure at the same firm are excluded from the sample since the variable Tenure is truncated at 15 for them.

Table 4b: (Log) Real Wage Regressions – Workers younger than 40 years at first interview Fixed Effects Estimation								
	Men			**Women**			**Pooled Men and Women**	
	All	*L*	*H*	*All*	*L*	*H*	*L*	*H*
Tenure	0.014 (0.002)	0.011 (0.002)	0.019 (0.004)	0.017 (0.003)	0.023 (0.004)	0.016 (0.004)	0.012 (0.002)	0.019 (0.004)
$Tenure^2$	-0.001 (0.0001)	-0.001 (0.0002)	-0.001 (0.0003)	-0.001 (0.0001)	-0.002 (0.0002)	-0.002 (0.0002)	-0.001 (0.0002)	-0.001 (0.0002)
Female*Tenure	---	---	---	---	---	---	**0.011** **(0.005)**	-0.003 (0.006)
Female* $Tenure^2$	---	---	---	---	---	---	-0.0007 (0.0005)	-0.0004 (0.0004)
N.obs	11940	8617	3323	6252	3381	2871	11998	6194

Notes: All regressions include also 6 dummies for region, 14 dummies for occupation, 2 dummies for industry and a dummy for work status (supervisor or not). Workers with more than 15 years of tenure are not included since the variable *Tenure* is truncated at 15 for them. In the last panel, when pooled men and women are taken together, all explanatory variables are interacted with *Female*.

Table 4c: (Log) Real Wage Regressions – Workers older than 40 years at first interviewed Fixed Effects Estimation								
	Men			**Women**			**Pooled Men and Women**	
	All	*Low*	*High*	*All*	*Low*	*High*	*Low*	*High*
Tenure	0.011 (0.004)	0.010 (0.004)	0.011 (0.012)	-0.003 (0.006)	0.003 (0.007)	-0.006 (0.014)	0.010 (0.004)	0.011 (0.011)
$Tenure^2$	-0.0005 (0.0002)	-0.0004 (0.0002)		0.0001 (0.0003)	-0.0001 (0.0004)	0.0007 (0.0005)	-0.0004 (0.0002)	-0.001 (0.0005)
Female*Tenure	---	---	---	---	---		-0.006 (0.008)	-0.018 (0.021)
Female* $Tenure^2$	---	---	---	---	---		0.0002 (0.0005)	0.002 (0.0009)
N.obs	2892	2394	498	1179	930	249	3324	747

Notes: All regressions include also 6 dummies for region, 14 dummies for occupation, 2 dummies for industry and a dummy for work status (supervisor or not). Workers with more than 15 years of tenure are not included since the variable *Tenure* is truncated at 15 for them. In the last panel, when pooled men and women are taken together, all explanatory variables are interacted with *Female*.

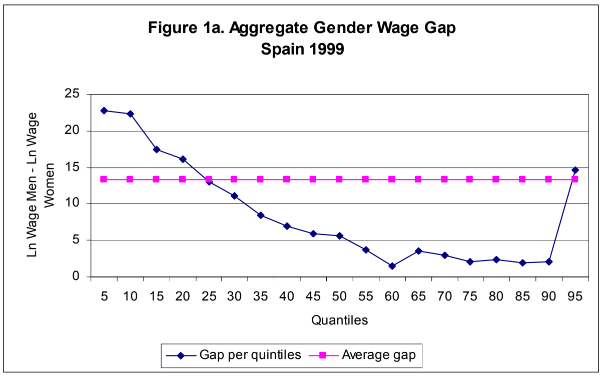

Figure 1a. Aggregate Gender Wage Gap
Spain 1999
Ln Wage Men - Ln Wage Women
Quantiles
Gap per quintiles
Average gap

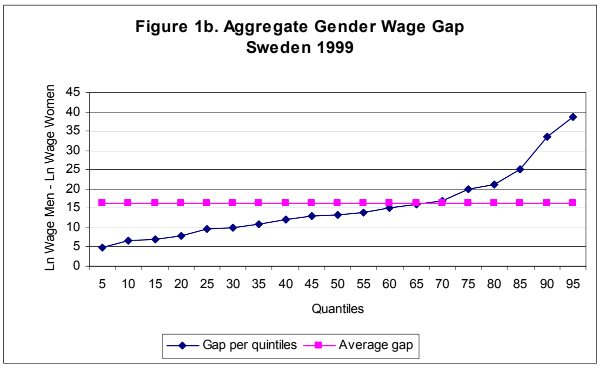

Figure 1b. Aggregate Gender Wage Gap
Sweden 1999
Ln Wage Men - Ln Wage Women
Quantiles
Gap per quintiles
Average gap

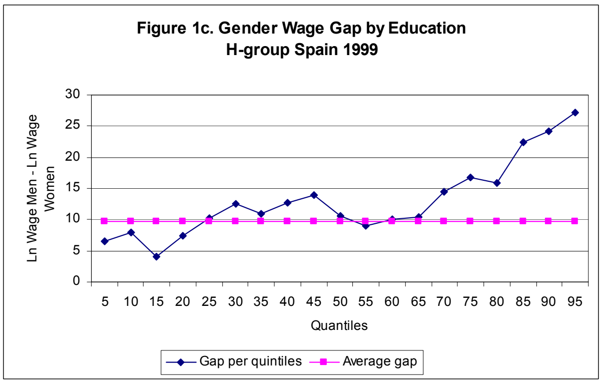

Figure 1c. Gender Wage Gap by Education
H-group Spain 1999
Ln Wage Men - Ln Wage Women
Quantiles
Gap per quintiles
Average gap

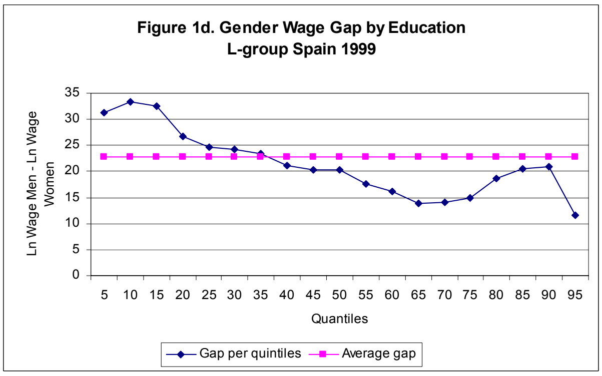

Figure 1d. Gender Wage Gap by Education
L-group Spain 1999
Ln Wage Men - Ln Wage Women
Quantiles
Gap per quintiles
Average gap

Figure 2a. Gender Wage Gap by Education
Denmark 1999

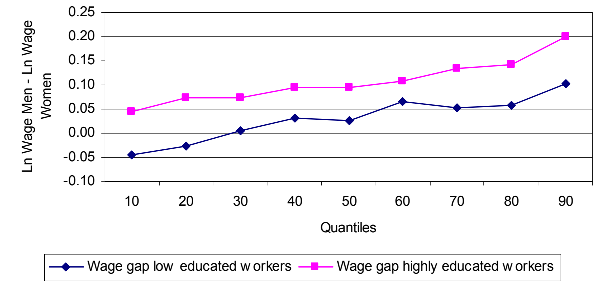

Figure 2b. Gender Wage Gap by Education
United Kingdom 1999

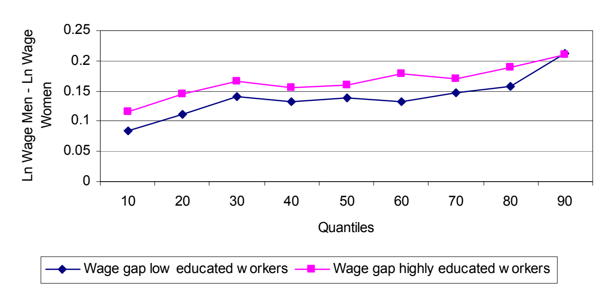

Figure 2c. Gender Wage Gap by Education
Greece 1999

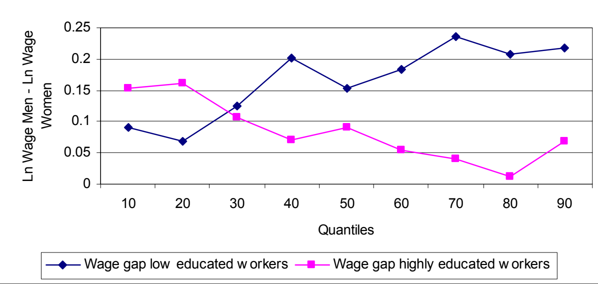

Figure 2d. Gender Wage Gap by Education
Italy 1999

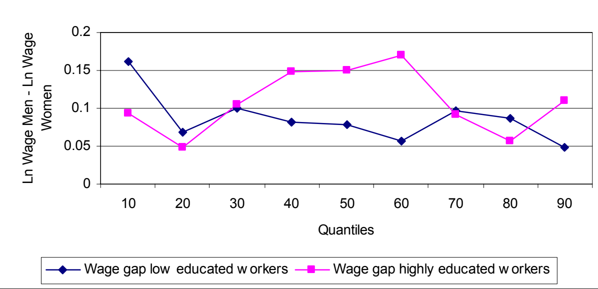

Figure 3a. Gender gap (Observed and Counterfactual). H-group. Spain 1999

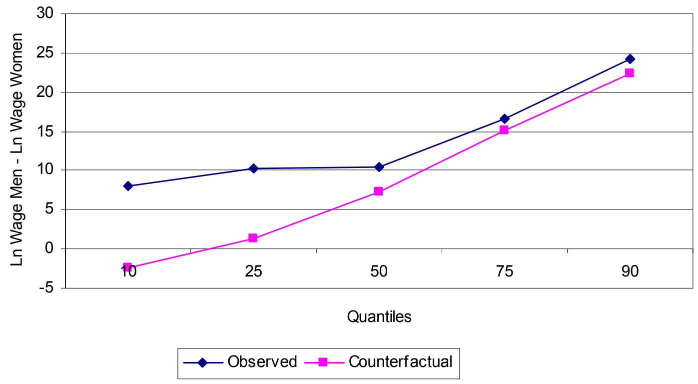

Figure 3a. Gender gap (Observed and Counterfactual). H-group. Spain. 1999