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RECent: c/o Dipartimento di Economia Politica, Viale Berengario 51, I-41100 Modena, ITALY
Phone +39 059 2056856, Fax +39 059 2056947, E-mail: RECent@unimore.it

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Tindara Addabbo and Donata Favaro

Tindara ADDABBO, Department of Economics, University of Modena and Reggio Emilia, Italy. Email: tindara.addabbo@unimore.it Affiliations: CHILD (Centre for Household, Income, Labour and Demographic Economics), http://www.child-centre.it/. CAPP (Centro di Analisi delle Politiche Pubbliche), http://www.capp.unimo.it. RECent, http://www.recent.unimore.it/

Donata FAVARO, Department of Economics, University of Padova, Italy. Email: donata.favaro@unipd.it.. Affiliations**:** CHILD (Centre for Household, Income, Labour and Demographic Economic) http://www.child-centre.it/. donata.favaro@unipd.it

Abstract

In this paper we evaluate wage differentials in Italy combining gender and education perspectives. The main goal of the article is to verify whether the extent of the gender pay gap varies between highly- and low-educated workers, and whether or not the role played by gender differences in characteristics and in market rewards is similar in the two groups. We apply quantile regression analysis and an adaptation of the procedure suggested by Machado and Mata (2005) to evaluate the predicted wage gap at different levels of education, at different points of the female wage distribution scale. The analysis is carried out on the Italian sample of the last available year of the European Community Household Panel (2001). We show that the extent and the trend of the gap predicted across the female distribution is sharply different between groups with diverse educational levels. In the case of low-educated workers, although the predicted gap is largely explained by differences in rewards, lower levels of education or experience are however responsible for the gap, especially on the right-hand side of the distribution. On the contrary, highly-educated females have better characteristics than highly-educated men that partially compensate the rather high difference in returns, in particular at the extremes of the distribution. It thus follows that the unexplained part of the predicted gap reveals a glass ceiling effect only for more highly-educated females.

JEL classification: J31, J71, C31
Keywords: Human capital, Gender wage differentials, Quantile regressions.

1. Introduction

The European Commission's most recent focus on gender earnings disparities, published in 2005 and based on the 2002 *Structure of Earnings Survey*, confirms the persistence of gender wage differentials across the EU with a marginal reduction compared to year 1995. The gender pay gap, defined as the average earnings of all full-time female employees divided by average earnings of all full-time male employees, calculated on gross hourly earnings, was equal to 77% in 2002, compared to 75% in 1995 (European Commission, 2005).

In explaining the extent of the gap, the European Commission turns its attention to the large role played in the occupational structure by sex and, furthermore, by gender differences in educational attainment that would appear exclude women from the best paid jobs. The level of education is still the most relevant selection criterion for non-manual jobs − especially at the top of the occupational hierarchy. On the opposite, when the educational level increases sharply for both sexes, men and women end up doing more similar jobs and occupations, as one would intuitively expect, and the gender wage gap decreases.

The European Commission's relevant point is that female-male wage gaps strongly depend on the type of occupation and, most of all, on the level of education. The fundamental matter for the European Commission is that both highly- and low-educated individuals, independently of sex, hold distinct skills and competences and enter different occupations; worker's educational levels strongly determine the type of occupation and the wage level individuals can aspire to and also the extent of gender wage differentials[1]. In Italy, the European Commission evaluates a gender pay gap, as defined above, of about 80%. In the comparative analysis, Italy comes across as one of the countries with the smallest extent of segregation and with a limited overall gender earnings gap. Relative earnings of women as a percentage of those of men are particularly high in those sectors that, on average, display the highest levels of earnings compared to other activities. Therefore, when Italian women reach those well-paid occupations, they suffer the lowest wage differentials with respect to their male colleagues.

An initial discussion on gender pay gaps by education, in line with the dichotomy between highly- and low-educated workers, was proposed by Katz and Murphy in 1992. Although the focus of that contribution was primarily on the evolution of relative wage changes between high school and college graduates though the 1960s, 1970s and 1980s, the study clearly showed that raw gender wage differentials can differ substantially between workers with different education levels, and that shifts in labour demand towards more educated workers can help to interpret changes in competitive skill prices. However, the study did not go into aspects related to the incidence on gender wage differentials of skill differences and skill prices, and did not evaluate the extent of the gap "unexplained" by differences in productive characteristics.

An initial study on gender wage differentials by education broken down in terms of differences in productive characteristics and in the rewards based on these characteristics has recently been carried out by de la Rica *et al.* (2008) on the

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[1] The drawback of the European Commission study is that much of the analysis is carried out on the raw wage gap, which incorporates the component of the differential attributable to female-male differences in productive characteristics.

Spanish sample of the European Household Panel Data (ECHP). As for the Italian case, an initial attempt to deal with gender wage differentials and education was discussed in Favaro and Magrini (2008), where young workers' gender wage differentials were analysed on matched employee-employer administrative data by means of a distributional approach.

In this article we follow on from the literature discussed above and provide an initial general evaluation of the Italian gender pay gap in relation to individual educational endowments, in line with the scheme arising from the literature on vertical earning differences between highly- and low-educated workers, which demonstrates that workers with different educational levels are destined to occupy working positions at different levels of competence; hence they are complementary in production and unevenly affected by market openness, the globalisation process and technological innovation.

The main aim of this article is to verify whether the dichotomy between highly- and low-educated workers does also imply, as expected, different patterns of gender pay gaps. The methodology we apply is a combination of econometric quantile estimation, in order to derive estimates of returns to individual characteristics across female wage distributions, and the Machado and Mata (2005) procedure in order to derive marginal distributions of predicted and counterfactual wages. By means of these methodologies, we are able to split the raw wage gap at any decile of the female marginal wage distribution into its components due to differences in characteristics or in rewards.[2]

The paper is structured as follows: in Paragraph 2 we discuss the main international literature on gender wage differentials adopting a distributional approach and the contributions on the role of education in explaining the gap. In Paragraph 3 we clarify the methodological issues and discuss the technique used to break down the wage gap across the distribution. The model is then estimated by using a sample of full-time employees drawn from the most recent available data from the European Community Household Panel (2001), as described in Paragraph 4. Results of the estimations and of wage gap decompositions are then presented in Paragraph 5.

2. Gender pay gaps across female wage distributions and educational attainment: recent empirical contributions in European countries

Research on gender wage differentials has been improved during the last decade by overcoming the Oaxaca and Blinder approach (Oaxaca, 1973; Blinder, 1973), whose pioneering contribution in the early 1970s legitimized the developing literature on the topic and brought in the fundamental distinction between the two components of the estimated pay gap: the one due to gender differences in productive characteristics and the second due to the differences in the rewards associated with those characteristics. The latest contributions to the topic (Juhn, Murphy and Pierce, 1993; Jenkins, 1994; Fortin and Lemieux, 1998; Machado

[2] For a methodological discussion on different approaches to the analysis of gender wage gaps, we suggest the report for the European Commission carried out by Beblo et al. (2003).

and Mata, 2005) all note (albeit with different propositions and goals[3]) the need for a gender comparison of pay gaps across the whole range of wages, and not only in correspondence with average values, as previously performed. These methodologies have led to substantial progress in the research, as they allow for the comprehension of how wage differentials are distributed right across female wage ranges, and present good potential for the identification of "fragile" occupational positions, and obstacles to wage progressions and occupational careers (different access to promotion). Applying the distributional approaches to the analysis of gender wage differentials has made it possible to highlight the uneven distribution of earning that penalises working women, especially affecting females whose earning capacity is either very low or higher than the average, shedding light on cases of the *glass ceiling* or *sticky floor* effects.

One of the first investigations on gender wage gaps across the distribution, applying the quantile regression analysis and a preliminary version of the Machado and Mata (2005) methodology[4] to derive marginal distributions of female predicted and counterfactual wages, was undertaken by Albrecht *et al.* (2003), in a study based on data from the Swedish Level of Living Surveys. Investigating the trend of the wage gap over time, the authors find evidence in favour of the existence of a glass ceiling pattern, and show that the gap at the top of the wage distribution, at least in Sweden, is a phenomenon of the 1990s.

[3] Juhn, Murphy and Pierce (1993), Fortin and Lemieux (1998) and the most recent contribution by Machado and Mata (2005) propose a comparison between female and male wages at different points of the distributions. Jenkins (1994), on the other hand, advises estimating female gaps individually and thereafter to analyse the distribution of those gaps.

[4] They had access to a preliminary version of the paper entitled "Counterfactual decomposition of changes in wage distributions using quantile regression", made available in February 2000.

Moreover, they demonstrate that high wage differentials at the top of the female wage distribution are mostly explained by differences in the rewards associated with different productive characteristics. In a later work, Albrecht *et al.* (2004) analyse the wage gap in the Netherlands on a sample of full-time workers selected from the 1992 Labour Supply Panel of the Dutch Institute for Labour Studies and applying quantile regression estimates taking the selection process for full-time work into account[5]. Their results are consistent with the existence, also in the Netherlands, of a glass ceiling pattern and a high incidence of gender differences in rewards. Moreover, they show that, when adjusting for selection into full-employment, the wage gap becomes larger, highlighting the occurrence of a strong positive selection into full-time work among women in the Netherlands.

The quantile regression methodology used to estimate earning functions in correspondence to different wage levels was also applied to Spain by Gardeazàbal and Ugidos (2005) on a sample selected from the 1995 Spanish Survey of Wage Structure[6]. They show that gender differences in terms of returns on characteristics are responsible for a higher gap at the bottom of the distribution. Garcìa *et al.* (2001), on the other hand, using a different dataset (the 1991 Encuesta de Conciencia, Biografia y Estructura de Clase) and correcting for non-random selection of women in employment and for the endogeneity of education, come up with the opposite result, e.g. an increasing wage gap moving from the bottom to the top of female wage distribution.

[5] Given the high proportion of Dutch women in part-time work, they control for full-time employment selection.
[6] The dataset covers employees in firms with ten or more workers and excludes the following production sectors: Agriculture, Public Administration, Health Services and Education.

Arulampalam *et al.* (2007) present quantile regression analyses on a sample of European countries[7] and study the wage gap in the private and public sectors separately. In most of the countries analysed (including Italy), they confirm the unequal incidence of the gap along the distribution of female wages, with wider wage differentials at top of the distribution scale. However, they show different extents of the wage gap between private and public sectors: higher wage gaps are found at both tails of the distribution of wages of private employees; in contrast, females working in the public sector suffer higher gaps only at the top of the distribution. This result holds true also in the Italian sample.

The above-discussed studies analyse the incidence of education on wage differentials by including individually attained educational levels among the explanatory variables of the wage equation. Education, in forming part of the productive characteristics of hourly wages, concurs as one of the components of the wage gap due to differences in characteristics, as well as of the wage differential ascribed to those characteristics' rewards. Conversely, Katz and Murphy's seminal work published in 1992, by studying raw wage differentials between men and women by educational level, clearly highlighted the role of education in determining the skill-content of occupations that individuals with different educational levels can access, and therefore, the existence of different earning capacities between highly- and low-educated workers. Katz and Murphy (1992) suggested that a separate study of highly- and low-educated worker's wages is meaningful.

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[7] A recent comparative analysis of gender average wage gaps and female employment can be found in Pissarides et al. (2005).

Only recently has Katz and Murhpy's proposition been taken up by de la Rica et al. (2008) studying Spanish wage differentials by workers' educational levels and decomposing the raw pay gap for each educational group into the two different components. De la Rica et al. (2008), using the sample of full-time workers selected from the 1999 cross-sectional Spanish data of the European Community Household Panel and applying the Machado and Mata (2005) methodology, show how the extent of the hourly wage gap follows two different patterns — along respective wage distributions — in the two subsamples considered: highly-educated women suffer a higher gap at the top of the distribution, while low-educated females are most penalised at the bottom. Moreover, in correspondence with the highest wage differentials, most of the gap is explained by differences in the rewards for certain characteristics. According to the authors, these results are consistent with the existence of a glass ceiling effect for highly-educated working women and of a sticky floor effect for the low-educated.

A different effort in the direction of studying the relationship between education and gender wage differentials is made by Favaro and Magrini (2008), who propose a distributional analysis of the wage gap based on the evaluation of bivariate density functions defined, as suggested by Jenkins (1994), on individual predicted and counterfactual wages. Using administrative data (supplied by the Italian Social Security Offices – INPS) on the universe of young workers employed full-time in some Italian provinces, the authors firstly estimate wage equations on the whole population in function of human capital and other productive characteristics[8]; they then evaluate both the extent of the unexplained wage gap and its probability of occurring by non-parametric estimates of bivariate density functions conditioned on human capital characteristics; the procedure makes it possible to derive bivariate probability distributions, defined on predicted and counterfactual individual wages, conditioned on different educational levels and human capital accumulated in the labour market. Favaro and Magrini show that highly educated young women suffer, in general, lower levels of wage discrimination than low-educated females; however, highly-educated women at the top of the distribution have been experiencing increasing wage gaps due to differences in rewards for characteristics ever since the end of the 1990s, showing the rise of the glass ceiling effect.

3. Methodological issues

The empirical investigation we carry out is based on the application of econometric quantile estimates ─ deriving decile values of returns on individual characteristics across female and male wage distributions ─ and the Machado and Mata (2005) procedure ─ obtaining marginal distributions of predicted and counterfactual wages. Once marginal distributions are constructed, we decompose the difference between female and male predicted wages, observed at any decile, into its components due to differences in estimated characteristics' rewards and to differences in characteristics evaluated at the relative decile.

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[8] Since the dataset does not include information on individual level of education, Favaro and Magrini construct a proxy of education by checking worker's first non-seasonal entrance into the labour market. In addition, they instrument education with a measure of the supply-side of the educational system .

The econometric procedure is developed by estimating quantile regressions on separate wage equations for female and male wage functions (Koenker and Bassett, 1982; Buchinsky, 1998), by assuming that wage functions are centred on different quantiles of the wage distribution; given the covariates vector *z*, estimates $Q_\theta(\omega|z)$ correspond to the θ-th quantile of the distribution of the log wage (ω), evaluated at any $\theta \in (0,1)$.

The quantile regression model is assumed to be linear:

$$\omega = z'\beta_\theta + u_\theta \tag{1}$$

Where ω is the log of wages, β_θ is a vector of coefficients, the quantile regression coefficients. The distribution of the error term u_θ is unspecified and it is simply assumed that $Q_\theta(u_\theta|z) = 0$.

The estimated values of the θ-th quantile of log wages, conditioned on covariates z, is equal to: $Q_\theta(\omega|z) = z'\hat{\beta}_\theta$. For the given $\theta \in (0,1)$, β_θ can be estimated by minimising in β_θ the following expression[9]:

$$n^{-1}\sum_{i=1}^{n}\rho_\theta(\omega_i - z_i'\beta) \tag{2}$$

where:

$$\rho_\theta(u_i) = \begin{cases} \theta u_i & \text{for} \quad u_i \geq 0 \\ (\theta - 1)u_i & \text{for} \quad u_i < 0 \end{cases} \tag{3}$$

[9] We estimate the vector of coefficients β_θ simultaneously, by means of the bootstrapping procedure that makes possible to test whether coefficients of different quantile regressions are significantly different pair-on-pair.

Following the above described procedure, we come up with estimated values of quantile coefficients for females ($\hat{\beta}_{\theta}^{f}$) and males ($\hat{\beta}_{\theta}^{m}$), at any θ-th quantile.

Given the estimated coefficients, we derive the marginal distributions of predicted and counterfactual female wages by applying the Albrecht *et al.* (2003) methodology.[10] Female predicted wages, at any point of the θ observation, are theoretical wages that female workers can earn given their characteristics and the estimated rewards recognised to those characteristics, $\hat{\beta}_{\theta}^{f}$; female counterfactual wages are wages that women would be paid if female characteristics were rewarded at male returns, $\hat{\beta}_{\theta}^{m}$.

In order to construct female marginal distributions, either predicted or counterfactual, along with the marginal distribution of male predicted wages, we proceed as follows:

- We draw on the female sample and construct predicted wages by multiplying characteristics z_f of every chosen individual by $\hat{\beta}_{\theta}^{f}$, at any θ. We repeat that operation N=100 times for all quantiles, ending up with the marginal distribution of female predicted wages, $z'_f\hat{\beta}_{\theta}^{f}$. We apply the same procedure to the male sample to obtain the marginal distribution of male predicted wages, $z'_m\hat{\beta}_{\theta}^{m}$. The difference between male and female marginal

[10] Albrecht *et al.* (2003) adopt a simplified version of the methodology proposed by Machado and Mata in a mimeo that was later published in the Journal of Applied Econometrics (Machado and Mata, 2005).

distributions, evaluated at any θ, represents the predicted gap, evaluated at decile θ and expressed in terms of female wages.

- We repeat the operation described above but apply male coefficients, $\hat{\beta}_\theta^m$, to female characteristics, to trace the marginal distribution of female counterfactual wages.
- We use female and male marginal wage distributions ($z'_f\hat{\beta}_\theta^f$ and $z'_m\hat{\beta}_\theta^m$ respectively) to evaluate the predicted wage gap in terms of female wages.
- We use female marginal and counterfactual distributions, $z'_f\hat{\beta}_\theta^f$ and $z'_f\hat{\beta}_\theta^m$, to evaluate the part of the predicted wage gap due to different gender rewards to characteristics.

4. Definition of the empirical model and categorisation of workers by education using ECHP information

The analysis is carried out on the sample of Italian employed workers aged 15 to 65, working full-time[11], selected from the 8th wave[12] of the European Community Household Panel (ECHP). As usual in the analysis of the wage gap, we focus on employed workers and do not take the self-employed into account, whose information on hours worked and earnings is hardly comparable to that of employees.

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[11] Part-time jobs are mainly held by women. The percentage of women employed part-time, out of the total employed, is 9.7% against 1.7% of men. We exclude part-time workers due to imperfect information in the ECHP, on the number of hours they effectively work.

[12] The most recent wave available, for the year 2001.

The model we estimate is a Mincerian wage equation in which the logarithm of the wage rate (gross hourly wage)[13] is assumed to be explained by individual productive characteristics, such as education and experience (general and specific); in addition, we include variables related to the demand side of the labour market (for instance size of the firm and activity sector), institutional features (such as contract type: permanent, temporary and other types of contracts), and macro-regional effects, summarising the incidence of market characteristics (such as local unemployment rate, availability of childcare services, etc.) on wage levels.

Our empirical model is similar to wage functions recently estimated on other countries' samples selected from the ECHP dataset (Arulampalam et al., 2007; de la Rica et al., 2008); however, since the dataset supplies information on the occupational content of jobs (principal activity performed and degree of responsibility), we include also controls for those aspects, whose relation to wage rates can be substantial.

The preliminary issue in a study by educational levels is which principle should be followed to categorise the sample; e.g. which educational threshold should be fixed to delineate educational sub-samples. Studies on the wage gap between highly- and low-educated workers, and on the effects that globalisation, international trade and migration have on inter-education wage gaps, commonly distinguished between workers with a university degree and workers with lower educational levels.

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[13] The wage rate is calculated following the procedure generally exploited when using the ECHP dataset: we divide (gross) monthly current wage and salary earnings from the main job by the number of weekly hours worked (in the main job) multiplied by the monthly standard number of weeks (4.3).

In our analysis we apply a different criterion, separating workers with a compulsory educational level from those with a higher level diploma. We chose this categorisation because it better fits the structure of the Italian educational system and the related occupational opportunities. In Italy, compulsory schooling sums a total of up to eight years, subdivided in two cycles: the first, up to five years of primary school (the so called "*scuola elementare*") and the second, three years of lower-secondary school ("*scuola secondaria inferiore*"). Individuals end the compulsory cycle, and decide whether to keep on studying when they are between 13 and 14 years old. If they decide to stay in school and enter the so-called upper stage of secondary education ("*scuola secondaria superiore*"), they can choose between different educational paths, some more technical-mathematical and other more humanistic. Whatever the case may be, if they complete the whole cycle of studies, they are allowed to enter university. This educational structure leads to quite a strong categorisation in the labour market between individuals with a compulsory educational level and those with a higher degree of study. As Table 1 shows[14], the former are mainly forced to enter low-skilled operative and blue-collar employment while the latter have access to clerical occupations and, if they have a university degree, may have better access to managerial positions.

[Table 1 here]

[14] All descriptive statistics and results reported in the paper are calculated on samples of individuals of 15-65 years old, employed full-time.

Highly-educated women are largely concentrated in the top three occupational categories: around 44% or women with post-compulsory levels of schooling work either as technicians, professionals, legislators, senior officials or managers. The proportion on the same occupations is slightly lower for highly-educated men and amounts to around 35%. On the contrary, the low-educated are misrepresented in top occupations: only 4% of women and around 3% of men.

In light of these considerations, we believe it appropriate to classify workers with a compulsory level of education as low-educated, and individuals with at least a post-compulsory school diploma as highly-educated. In international terms, this corresponds to distinguishing between educational levels ISCED 0-2 and ISCED 3-7. Given this categorisation, the information available in the ECHP dataset makes it possible to define some control dummies for individuals with a third level of education (ISCED 5-7) that will be included in the estimates related to the highly-educated group.

Figure 1 shows kernel density functions of hourly wages of men and women employed full-time (aged 15-64), based on the educational groups defined above; the distance between men and women's distribution densities at any point represents the extent of the raw gap. In both groups, the differential is in favour of men, although its extent is sharply higher for low-educated than for highly-educated women at any wage level, as it is clear from Table 2, which summarises information on the raw gap, the predicted gap and its components, and which will be discussed later.

[Figure 1 here]

Now we go through the estimation procedure and the discussion of the decomposition of the predicted wage gap.

In a Mincerian-type wage equation, much of the role in explaining wage rates is attributed to human capital components, in particular education and experience. As previously explained, the subsample of low-educated workers is pretty homogeneous; the highly-educated subsample, on the other hand, includes workers with either a second stage of secondary level or tertiary level education. Therefore, to the wage equation we add a dummy to capture the effect of any type of university degree.

With regard to human capital other than formal education, the information available in the dataset allows us to construct two different variables: one for general experience (labour market experience) and a second for firm-specific experience. We are able to compute experience accumulated in the labour market in terms of the total number of years spent working, in theory, since the first employment. This is a continuous variable and, as is generally assumed, enters the wage equation in quadratic form to capture its increasing effect, but to a decreasing degree, on wages.

A degree of caution is generally advisable when using such a "theoretical" measure of experience, which may not correspond to the effective years spent in the labour market. Indeed, that proxy does not take into account periods of absence from the labour market, due to unemployment, inactivity, or simply illness or parenthood. If this were the case, theoretical experience would overestimate the real number of years of working activity. This measurement problem arises in both the male and female samples; however, as empirical evidence shows, the problem is more serious for females, due to interruptions caused by maternity leave. For that reason, we partially solve this issue by adding the interaction of experience with the number of children among the explicatory variables. While it is true that having children implies a certain interruption of working activity and as well as a degree of penalisation in terms of experience, we should detect a negative impact of that variable on the level of wages. However, since gross wages include components of maternity allowance, we may even detect some positive effect with regard to low levels of income, for which financial assistance for childcare systems is provided.

A relevant part of workers' experience is built up inside the firm and assumes a more specific skill base than general knowledge. Therefore, we include among the regressors the variable "tenure" by using the available information on the number of years spent in the firm. However, the ECHP dataset supplies information on the exact period spent with the current employer if less than 15 years; longer periods are registered only by classes. In order to use a homogeneous measure of tenure (independently of the tenure period) and not to exclude any observation from the dataset, we construct different dummies taking the value of 1 if the period is five years or less, between six and ten years, between eleven and fifteen years or more than sixteen years[15].

[15] We checked for a correlation between the variables of "experience" and "tenure". An intital check was carried out on the continuous variables, for the subsample of workers with less than 15 years of company service; correlation levels in that case amount to 0.5 both for females and males when highly-educated, falling to 0.25 for low-educated women and to 0.15 for low-educated men. The correlation evaluated between experience and tenure dummies (the specification we use in the

Among the regressors we also include variables related to productive sectors[16], firm size and occupational characteristics; moreover, unlike previous analyses of gender wage differentials carried out on the ECHP, we add control elements for each occupational category, in order to reflect differences in wages due to professional characteristics[17]. Finally, using information on the employee's position in her/his business or organisation, we also check for the degree of responsibility s/he declares to have in her/his job. The worker is asked if s/he supervises or co-ordinates the work of any personnel and, if so, whether s/he has any say in their pay or promotion. On the base of those questions, the database defines a categorical variable with value zero if the worker declares not to have any supervisory or co-ordination position in the business, value 1 if s/he answers positively to the first question, but negatively to the second, and value 2 if the interviewee answers positively to both questions. This information allows us to define three dummy variables capturing the degree of supervision in the work place: a high, an intermediate and a non-existent supervisory role.

To complete the model specification, we include variables related to bargaining characteristics, distinguishing permanent employment from fixed- or short-term

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estimates) is mainly negative, and in absolute value is lower than 0.5 for both sexes, independently of educational levels. Correlation becomes positive and assumes values around 0.6 only for women and men with tenure longer than 15 years; still, it is not a high level.

[16] Public versus private sector and economic aggregates versus private sectors: agriculture, industry and services.

[17] We refer to the International Labour Office classification. The profession of reference is "Sales and services elementary occupations". Dummy variables are included for the following occupational categories: physical, mathematical, engineering, life science and health professionals, teaching professionals, other professionals; physical, mathematical, engineering, life science and health associate professionals, teaching and other technical professionals; office and customer services clerks; personal and protective services workers; models, salespersons and demonstrators; skilled agricultural and fishery workers; craft and related trades, and extraction and building trade workers; metal, machinery, precision, handicraft, craft printing and related trades workers.

jobs and other types of contracts[18], and macro-regional dummies to capture territorial differences due to different bargaining rules and labour market contexts.

A summary of the statistics of the variables used in the estimates is to be found in the Appendix (Table A1). In average terms, the raw hourly gap is against female workers, for both educational levels, and it is significantly higher in the case of low-educated than highly-educated women: highly-educated women suffer, on average, an 8% gap, against a 14% one in the case of the low-educated. However, observing Figure 1 and Table 2, we may also note that the range of the wage gap across the distribution is notably different between highly- and low-educated women; in the former case the gap oscillates between 5.9% and 11.3%, while in the latter case it varies between 7.2% and almost 18%. In general, while highly-educated women narrow the gap when moving from the lowest deciles to the median value of the distribution, and lose that gain when they reach higher wage levels, wage differences between low-educated females and males show an increasing path up to the fifth decile before tending to diminish as women move towards the best rewarded positions.

With regard to human capital characteristics, we may observe a slightly higher proportion of women than men with a tertiary educational level. Since the sample includes employees up to 65-year-old, this figure confirms the substantial educational upgrading of young females. On the other hand, as to other human capital characteristics accumulated after formal education (e.g. experience and tenure), men register the highest average levels.

[18] We summarise in the "other types of contract" category the categories defined by the ECHP as "casual work with no contract" and "other arrangements".

A few other remarks on sample characteristics are interesting to note. Firstly, independently of the educational level, women are more concentrated in small firms than men are, and are more likely to be employed with fixed-term or short-term contracts. However, being highly-educated facilitates access to permanent occupations: the frequency of temporary contracts decreases when workers, either male or female, are highly-educated.

5. Decomposing the wage gap across the distributions

In this section, we shall discuss the main results of the econometric analysis, through which we determine the estimates of the rewards to the characteristics and obtain predicted hourly wages for men and women, evaluated at any decile level by means of quantile regressions. After that, we shall examine the marginal distribution of female and male wages, acquired by means of the Machado and Mata procedure discussed in Paragraph 3, and decompose the predicted gaps across the distributions into two components: one ascribed to differences by gender in productive characteristics (the "explained" part of the gap), the other due to differences in returns for the same characteristics (the "unexplained" part of the gap). The discussion of the results of both the econometric analysis and the gap decomposition will highlight the appropriateness of studying gender wage differences by educational levels. At least in the Italian case, there are glaring differences by education in the extent of the gap and the contribution of the different components across the wage distribution.

The econometric model has been already explained in Paragraph 3; we might only point out that unlike wage regressions previously carried out on ECHP, our specification includes professional categories and the degree of responsibility assumed by the individual in her/his job.

Estimation results are shown in the Appendix (Tables A2 and A3). We may note that the first relevant differences between highly- and low-educated workers emerge as to the rewards for human capital characteristics: independently of sex, both general and specific experience and the degree of responsibility on the job significantly concur to determine wage levels across the distribution of most educated workers. However, we may assert that human capital characteristics do not contribute substantially to the determination of the wages of low-educated workers, either men or women; in that case, the primary role in determining wage levels seems to be played by what we may call institutional factors, such as the economic sector of activity, the contractual framework, firm size and regional context. The difference between the two groups of workers is supported by the analysis on the statistical significance of the test on the equality of coefficients evaluated at different deciles, carried out for every estimated parameter considered individually, and for the set of human capital coefficients considered jointly.[19]

The results of the investigation carried out on the set of human capital variables are shown in Table A4 in the Appendix; they appear to back up the use of the quantile regression methodology, in particular with reference to the group of the highly-educated. For the subsample of these workers, the values of the tests reject

[19] The test on the significance of the difference between decile coefficients has been carried out on every single variable, in order to verify the usefulness of carrying out quantile regressions. We do not quote all the results due to space limits; instead, we opted for the shorter solution of discussing tests on the difference between couples of decile parameters on the set of human capital coefficients. We can supply the complete analysis on request. At any rate, we may assert that the complete analysis on the difference between decile coefficients has proved the need to estimate quantile regressions.

the hypothesis of equality between different decile levels of all human capital coefficients; decile estimates appear significantly dissimilar for both sexes, not only between left and right-hand sides of the distributions but also between different deciles of the same distribution tail. Such differences are less pronounced across the wage distributions of low-educated workers; in this case, rewarding human capital characteristics is significantly different, especially between lower and upper deciles of the distributions.

As for highly-educated workers, we might occupy a few lines briefly commenting on the estimated results. For this group of workers, the type of human capital accumulated after formal education plays a role of great relevance in explaining wage upgrading by gender; in line with the evidence emerging in the literature on gender wage differentials carried out in other countries and with the few studies on Italy, we find that male wages are more sensitive to general experience − accumulated in the labour market − than to specific human capital built up in the firm where working at present; on the contrary, female wage upgrading strongly depends on specific experience. Going into detail, the return to general experience is positively significant for men, even though decreasing with the rise of the wage rate and insignificant at very high wage levels. On the other hand, it is only slightly significant for women, and only in correspondence to the first decile of the distribution and around the median value, its value furthermore being half that of men.

Turning to the rewards for specific experience, measured by the permanence in the firm (variable “tenure”), our results appear to outline the existence of different models of economic reward by gender. Male workers are able to obtain a gradual increase in wages as the period of permanence in the firm increases, and that upgrading is recognised as from short periods of tenure. On the contrary, females achieve statistically significant rewards if the period of permanence in the firm becomes particularly long, precisely longer than ten years; indeed in that case, returns are higher than what men receive. Likewise, if male workers have supervisory roles in the firm, they get incremental rewards as coordination tasks become more relevant. On the other hand, female workers with supervisory positions are able to achieve economic gratification for that position only if they get the highest degree of coordination or supervision of any personnel, corresponding to having a say in their own pay or promotion.

The estimated coefficients are applied to obtain female and male distributions of predicted wages − wages that men and women can earn given their respective characteristics − as explained in Paragraph 3. Since we express wage rates in logarithms, the difference between any male and female decile values of predicted marginal distributions is explicative of the gender percentage gap predicted at that point of the distribution, in terms female wages. For example, a 0.15 difference means that male wages are 15% higher than female wages[20].

We break down the predicted gap, evaluated at different points of observation, into its components (as originally defined by Oaxaca (1973) and Blinder (1973)) only by the mean wage value: the component due to gender differences in productive characteristics and the part owed to differences in their rewards, the so-called unexplained part of the gap. To evaluate the unexplained component of the

[20] A positive value states a wage gap in favour of men and, conversely, a negative wage gap points to wage differentials in favour of women.

estimated wage gap, we construct counterfactual wages, i.e. wages that females might earn if their characteristics were rewarded as males' are, as illustrated in Paragraph 3.[21] In accordance with the estimation procedure carried out for each decile of the original wage distributions, the predicted wage gap has been partitioned in its factors in correspondence with each decile of female and male predicted wage distribution.

The figures included below summarise the whole analysis discussed up to this point. Apart from representing the results for highly- and low-educated workers separately, in accordance with the focus of the paper, we include a Figure for the whole sample of workers − the pooled model − (where highly- and low-educated workers enter indistinctly) to highlight how the results might have been if we had carried out the analysis on the whole sample of workers − without distinguishing between highly- and low-educated − as is usually done in the literature on the decomposition of the gender wage gap.[22] The error in evaluating wage differentials could be quite relevant if the two differently educated groups were jointly considered; on the other hand, separating by education makes it possible to recognise sharp dissimilarities between the two groups.

Each Figure displays the extent, across deciles, of the raw gap (discussed in Paragraph 2), the predicted gap, and its "unexplained component", put down to

[21]The decomposition we discuss in this article is in terms of female wages and allows us to evaluate the gap women experience, the component due to gender differences in characteristics aside, i.e. the difference between their predicted wage and the wage they may earn if they were paid at males' returns. Decomposing the wage gap in terms of male wages and, therefore, evaluating the unexplained part of the gap in terms of male characteristics, in a context where female characteristics are in general better than male characteristics, would overestimate the component of the gap due to differences in returns.

[22] The decomposition, in this case, is carried out on quantile estimates performed on the whole sample of workers, including both highly- and low-educated. We do not include those quantile estimate results in the Appendix because not in the objective of the paper. However, we would be glad to provide those results on request.

gender differences in rewards for productive characteristics. In Table 2 we show the decile values of the wage gap in detail, and evaluate the part of the predicted gap at each decile due to differences in gender characteristics or rewards.

[Figures 2, 3, 4 here]

The comparison of the three Figures underlines the relevance of our research focus; it is evident that the wage gap, be it raw or predicted, follows different paths in the two groups considered and that, if the study were carried out on the whole sample, predictions on its trend across the distribution would have been completely different. Moreover, the analysis by education highlights the distinctive role played by gender differences in productive characteristics and those characteristics' rewards in explaining the predicted wage gap.

Considering the whole sample (Figure 2), the decreasing trend of the predicted gap across the female wage distribution would lead us to conclude that women experience a wage gap that decreases as they reach higher wage rates, and becomes positive at the upper limit of the distribution, in correspondence with the highest distribution decile. In addition to that, the decomposition procedure would lead us to conclude that women have much better productive characteristics than men have, and that the gap component due to differences in those factors explains a predicted wage gap in favour of women; moreover, female characteristics improve more than male characteristics do as wage levels increase, and therefore, the part of the gap explained by differences in characteristics becomes even more in favour of women, reaching more than 14% at the highest wage levels. On the other hand, in correspondence to the same wage deciles, the unexplained part of the gap amounts to almost 13% in favour of male workers (differences in rewards are highest at the extremes of the distribution). In conclusion, through a "pooled" analysis we would predict that female losses decrease as women reach the highest earnings levels; furthermore, female productive characteristics, by increasingly counterbalancing differences in rewards across the female wage distribution, allow women to turn the predicted wage gap to their favour at the highest wage rates.

Those results are in line with the only existing analysis on Italy carried out on the ECHP using quantile regressions, the work of Arulampalam et al. (2007), who study gender wage gaps in the European countries by splitting the sample according to the sector of activity, be it public or private. Arulampalam et al., before proceeding in separate estimates between public and private sectors, briefly discuss the results of a pooled model including all workers (page 169). Their estimates, differently from ours, do not include occupational and sector dummies among the explicative variables, and it is probably for that reason that they obtain slightly higher predicted wage differentials and a larger percentage of the gap is explained by different returns. However, although our "pooled" model estimates well predict the raw gap (see Figure 2) and the decomposition outcomes are akin to the results of Arulampalam et al. (2007), they conceal striking differences between highly- and low-educated workers, as may be clearly observed comparing Figure 2 to the subsequent Figures.

Figures 3 and 4 represent the trend of the gap across the deciles of distributions for highly- and low-educated female workers, considered separately, whose estimates are discussed above; they clearly show how the raw measure of the pay gap follows distinct patterns across the distributions of highly- and low-educated females, which would not be well represented by the pooled measures illustrated in Figure 2. In particular, in the case of low-educated females, the raw gap follows an increasing trend up to the median wage level, rising from 7% to 15.6%; after wards which it fluctuates but tends to decrease, reaching 12.7 percentage points, always in favour of males. If highly-educated, female workers suffer a wage gap against that is slightly higher than the wage gap affecting low-educated, at the lowest deciles of the distribution: the wage gap for highly educated amounts to 10.5% at the bottom tail of the wage distribution. However, unlike what we observe for low-educated women, the raw gap decreases as women upgrade in terms of earnings capacity and tends towards a level of less than 6% at the seventh decile. Conversely, the gap grows again at the highest wage levels, reaching more than 11% at the top of the distribution.

The predicted gap, contrary to what would emerge from only a pooled estimation, turns out to increase generally in both subsamples, although to a different extent. Low-educated females with especially low pay levels have predicted gaps around 11% and 12% and the gap rises as wages increase, reaching 16% at the eighth decile; after which, the predicted gap undergoes a sharp decline, falling to 12.7% at the highest decile value. On the contrary, the predicted gap for highly-educated women initially decreases from 8 to 5% (between first and second deciles) and then turns back up to the seventh decile, reaching the highest magnitude at around 10%. Then, at the top of the distribution the estimated value of the gap slightly fluctuates, with a clear upwards change at the highest decile (of about 2%), capturing the trend in the raw gap. In general, the extension of the pay gap for highly-educated women is 7-8% lower than it is for the low-educated.

The most substantial differences between highly- and low-educated workers arise when decomposing predicted gaps. Looking at low-educated females, the part of the gap attributed to differences in characteristics' rewards is lower than the predicted gap; in this case, across the whole wage distribution, gender differences in returns do not cover the whole prediction, meaning that part of the differential is explained by female productive characteristics, less than those that men have. That is particularly true at wage rates higher than the median value: low-educated women reaching the highest pay levels are not able to match male income profiles also because of their productive characteristics. However, better male characteristics are able to account for maximum 4.5% of the gap against women once at the eighth decile; indeed, across most of the distribution, the part of the gap explained by differences in characteristics in favour of men is lower than 2% and are cancelled at between the forth decile and the median value. At those points, females have productive characteristics similar to their male colleagues and the predicted gap coincides exactly with the gap due to differences in rewards.

[Table 2 here]

As for the results for highly-educated females, we note that the estimates of the gap imputed to differences in rewards for characteristics are steadily higher than the whole predicted gap, across the whole range of wages. In this case, at any wage level, female characteristics would explain wage differentials in favour of women, but this female advantage is eroded completely by differences in rewards. That is, independently of the wage level, highly-educated women experience gaps in rewards that more than compensate for the positive difference due to productive characteristics. Moreover, the gap in returns rises as wage rates increase, shifting from 8% at the bottom of the distribution to 14% at the top, and as a consequence, the economic advantage due to better characteristics is reduced itself as women upgrade their wage rates.

The sharp difference we detect in the composition of the predicted wage gap by education and the high incidence, in the case of highly-educated women, of differences in characteristics' rewards may suggest the possibility that highly-educated Italian women are overeducated, or at least more overeducated than males, and that the pay penalty they suffer compared to their well-matched counterparts is higher than that experienced by males. This is a result that has been detected in other countries, for example in Northern Ireland by McGuinness and Bennett (2007), who study a sample of students completing a Higher Education programme, and find that overeducated males earn 11% less than their well-matched counterparts while overeducated females earn almost 23% less than adequately matched females.[23] As for Italy, Di Pietro and Urwin (2006)[24] find that Italian graduates whose level of education exceeds the adequate or formally required level of education for their job receive lower wages than their peers with

[23] On the other hand, Groot (1996), studying a sample of British wage–earners of all educational levels, shows that in Britain the allocation of female workers is more efficient than the allocation of males and that the probability of being overeducated decreases with work experience. In this case, the result is likely to depend on the fact that workers of different educational levels have been considered together.

[24] They study a sample of individuals who graduated from all Italian universities in 1998.

a similar level of schooling in jobs for which they are suitably qualified. Unfortunately the authors do not present a gender analysis of the phenomenon.

In conclusion, through our study we find that in the Italian case the pattern of female/male wage differentials is different between highly- and low-educated women and that a glass ceiling effect is detected only for highly-educated women, whose gap follows a steadily increasing trend across the whole distribution but especially at the top. Notwithstanding this, at those wage levels the predicted gap stabilises and even tends to decrease slightly, as a result of the good productive characteristics of highly-educated women earning top wages.

In contrast, we do not detect either a glass ceiling or a sticky floor effect across the wage distribution of low-educated women; we observe in this case an increasing trend in both the predicted gap and the component due to differences in rewards as women upgrade from very low wage levels to the median value. On the other hand, the wage gap attributed to differences in rewards decreases as women approach wage levels higher than the median wage and, in particular, the top of the distribution.

Our results differ somewhat from recent studies on gender wage differentials that analyse pooled samples of workers without splitting by education; in general they detect a disadvantage for all female workers due to differences in rewards that exceed the predicted gap. On the other hand, our study confirms part of the results of de la Rica et al. (2008) and the results of Favaro and Magrini (2008), who find different outcomes conditioned on education and a glass ceiling effect respectively for highly-educated women in Spain[25] and for young highly-educated females working in the Italian Venetian region.

6. Conclusions

Our study arises from the interest in analysing gender wage differentials in Italy along the lines of a distributional approach, with the aim of verifying whether education affects the wage gap and its composition. The article contributes to the literature on the empirical analysis of gender wage differentials by means of distributional approaches. In this case, we apply quantile regression analysis and the Machado and Mata (2005) procedure to derive marginal distributions of female and male wages and the predicted gap. We then decompose that gap, at every decile of female wage distribution, in the component due to gender differences in characteristics and rewards.

The analysis shows that female to male wage differentials in Italy strongly depend on workers' education attainment: highly-educated women are affected by lower wage gaps than low-educated women, at any wage rate. Our outcomes predict a wage loss of women relative to men between 4.8% and 11.3% if highly-educated, and between 11.7% and 16.1% if low-educated. Moreover, the trend of the gap across the female wage distribution is rather different between the two groups: whereas the predicted gap of low-educated women tends to increase across the first part of the distribution and to settle around 15% at the median point, highly-educated women's predicted gap steadily raises from low to top wages, reaching

[25] They also find a sticky floor pattern in the sample of low-educated females.

around 16% at the eighth decile. It then slightly decreases among the very top of wages.

The most interesting results are found when we evaluate the contribution to the gap of gender differences in characteristics and rewards: the decomposition procedure highlights relevant differences between differently educated workers. In the case of low-educated workers, female to male wage gaps depend on both higher rewards to male productive characteristics, compared to females, and lower female productive characteristics; the predicted gap is partially explained by a poorer composition of the female sample as compared to the male one, especially at high wage rates. Indeed, the wage gap attributed to gender differences in rewards reaches a maximum of around 15%. On the contrary, the component of the highly-educated wage gap ascribed to differences in rewards exceeds the predicted gap at any wage level; in this case, female characteristics are better than male ones, in particular at the left-hand end of the distribution. Therefore, the unexplained part of the predicted gap ranges between 8% and 14%.

As to the existence of a glass ceiling or a sticky floor effect in female Italian wage pattern, our analysis highlights the persistence of a glass ceiling effect only for highly-educated women. On the other hand, we do not detect a sticky floor pattern in any group.

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Figures and Tables

Figure 1. Wage distributions by educational achievement and gender

Figure 2. Raw gap, predicted gap and gap due to differences in returns. All females

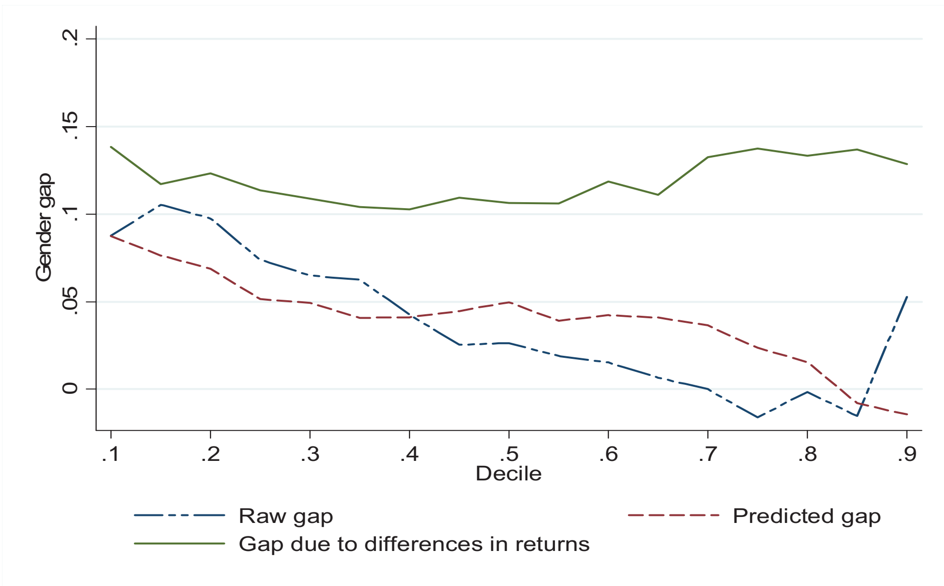

Figure 3. Raw gap, predicted gap and gap due to differences in returns. Highly-educated females

Figure 4. Raw gap, predicted gap and gap due to differences in returns. Low-educated females

Table 1. Type of occupation in current job. Distribution by education and gender (%)

	Highly-educated		Low-educated	
	Women	Men	Women	Men
Legislators, senior officials and managers	0.59	4.49	0.26	0.49
Professionals	26.97	11.87	0.51	0.10
Technicians and associate professionals	16.63	19.09	3.58	2.34
Clerks	38.39	27.83	15.86	7.50
Service workers and shop and market sales workers	10.04	8.26	18.67	10.33
Skilled agricultural and fishery workers	0.00	0.88	2.81	3.31
Craft and related trades workers	2.85	13.31	21.74	37.23
Plant and machine operators and assemblers	1.67	9.46	10.23	18.52
Elementary occupations	2.85	4.81	26.34	20.18

Our elaborations on ECHP data (Italian sample).

Table 2. Wage gap decomposition by decile and educational level (%) expressed in terms of females' wages*

	All females				Highly-educated				Low-educated			
Decile	Raw gap	Predicted gap	Differences in		Raw gap	Predicted gap	Differences in		Raw gap	Predicted gap	Differences in	
			returns	characteristics			returns	characteristics			returns	characteristics
0.1	8.78	8.73	13.83	-5.10	10.54	7.95	8.35	-0.40	7.21	11.71	11.77	-0.05
0.2	9.76	6.88	12.34	-5.46	6.50	4.76	9.13	-4.37	13.30	12.77	11.23	1.54
0.3	6.50	4.94	10.88	-5.93	8.00	4.86	9.03	-4.16	15.89	13.57	11.67	1.90
0.4	4.27	4.11	10.27	-6.16	6.25	6.45	10.10	-3.64	17.77	13.80	13.89	-0.10
0.5	2.64	4.97	10.64	-5.67	6.90	8.39	11.21	-2.82	16.89	15.64	14.45	1.19
0.6	1.53	4.22	11.86	-7.64	6.33	9.12	12.34	-3.22	14.63	15.07	14.48	0.59
0.7	0.00	3.65	13.24	-9.60	5.92	10.20	12.95	-2.75	16.60	15.55	13.42	2.12
0.8	-0.16	1.55	13.34	-11.79	9.18	9.48	14.99	-5.51	16.03	16.11	11.59	4.52
0.9	5.27	-1.45	12.87	-14.32	11.94	11.29	14.14	-2.85	12.72	12.73	10.08	2.66

** A positive value of raw or predicted gaps means a wage gap to the detriment of women. A positive difference in characteristics means that female characteristics are poorer than those of men. A positive difference in characteristics' rewards indicates that returns are higher for men than they are for women.*

Appendix

Table A1. Sample descriptive statistics

	Low-educated				Highly-educated			
	Women		Men		Women		Men	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Log hourly wage	2.45	.33	2.59	.32	2.79	.42	2.87	.43
Married/cohabiting	.63	.48	.71	.45	.64	.48	.66	.47
Upper-stage of secondary education	-	-	-	-	.78	.41	.80	.40
University education	-	-	-	-	.22	.41	.20	.40
Experience	18.09	10.96	20.01	11.80	14.45	9.92	15.63	10.40
Experience squared/10	44.71	43.47	53.91	51.58	30.72	34.25	35.27	36.96
Experience*Children	3.74	7.45	7.26	10.40	5.14	8.00	6.22	9.29
Intermediate supervisory level	.08	.27	.10	.30	.13	.33	.21	.41
High supervisory level	.03	.17	.05	.21	.07	.26	.17	.37
Tenure 6-10 years	.14	.35	.12	.32	.15	.36	.16	.36
Tenure 11-15 years	.12	.33	.10	.30	.11	.32	.11	.31
Tenure more than 15 years	.31	.46	.33	.47	.34	.47	.36	.48
Public Sector	.19	.39	.23	.42	.55	.50	.39	.49
Agriculture	.06	.24	.07	.25	.00	.05	.02	.15
Services	.59	.49	.44	.50	.87	.33	.65	.48
Fixed-term or short-term contract	.11	.32	.07	.26	.07	.26	.05	.22
Other contract	.09	.29	.08	.27	.03	.16	.02	.02
Firm size: 5-19 employees	.36	.48	.32	.47	.27	.44	.24	.24
Firm size: 20-49 employees	.16	.37	.13	.34	.17	.38	.19	.19
Firm size 50-99 employees	.08	.28	.08	.27	.12	.32	.12	.12
Firm size: 100-499 employees	.11	.31	.11	.31	.15	.36	.170	.17
Firm size: more than 500 employees	.06	.24	.09	.28	.09	.29	.15	.15
North-west	.08	.28	.07	.25	.12	.32	.10	.10
North-east	.16	.36	.01	.29	.12	.32	.11	.11
South and Islands	.20	.40	.35	.48	.25	.43	.28	.28

Source: *Descriptive statistics on ECHP 2001 sample*

Table A2a. Quantile regressions. Highly-educated women

	10th	20th	30th	40th	50th	60th	70th	80th	90th
Married/cohabitating	.022 (0.59)	.035 (1.00)	.026 (0.83)	.022 (0.74)	0.26 (0.89)	.026 (0.90)	.017 (0.63)	.019 (0.62)	.051 (1.45)
University education	.123 (2.82)	.144 (3.20)	.175 (4.45)	.186 (5.28)	.184 (4.39)	.228 (5.50)	.281 (6.96)	.322 (6.97)	.279 (4.95)
Experience	.013 (1.65)	.006 (0.89)	.008 (1.42)	.008 (1.69)	.007 (1.66)	.007 (1.48)	.003 (0.56)	.002 (0.28)	.005 (0.56)
Experience squared	-.000 (-1.35)	-.000 (-0.33)	-.000 (-0.78)	-.000 (-1.23)	-.000 (-1.16)	-.000 (-0.59)	.000 (0.14)	.000 (0.37)	-.000 (-0.46)
Experience*Children	-.0032 (-2.03)	-.001 (-0.76)	.000 (0.13)	.000 (0.08)	.001 (0.66)	.002 (0.93)	.002 (1.12)	.002 (1.03)	.001 (0.69)
Intermediate supervisory level	.074 (2.13)	.034 (1.13)	.034 (1.08)	.047 (1.52)	.037 (1.31)	.022 (0.73)	.017 (0.49)	.010 (0.23)	.049 (0.95)
High supervisory level	.133 (2.52)	.101 (1.96)	.068 (1.29)	.107 (1.87)	.144 (2.53)	.139 (2.39)	.146 (2.33)	.224 (3.03)	.291 (3.34)
Tenure 6-10 years	.079 (1.61)	.062 (1.25)	.045 (1.06)	.059 (1.66)	.051 (1.45)	.055 (1.53)	.056 (1.33)	.060 (1.23)	.049 (0.78)
Tenure 11-15 years	.203 (3.66)	.131 (2.72)	.049 (1.09)	.063 (1.48)	.069 (1.68)	.065 (1.61)	.070 (1.84)	.057 (1.37)	.024 (0.38)
Tenure more than 15 years	.171 (2.96)	.126 (2.25)	.073 (1.35)	.064 (1.46)	.084 (1.94)	.099 (2.16)	.104 (2.38)	.133 (2.62)	.154 (2.34)
Public sector	.192 (4.45)	.163 (4.46)	.129 (3.85)	.133 (4.43)	.118 (3.62)	.092 (2.78)	.062 (1.86)	.032 (0.82)	-.028 (-0.59)
Agriculture	-1.057 (-1.73)	-.1.159 (-1.93)	-1.128 (-1.91)	-1.152 (-2.01)	-.238 (-0.45)	-.252 (-0.51)	-.381 (-0.86)	-.498 (-1.18)	-.563 (-1.38)
Services	-.018 (-0.35)	.011 (0.20)	-.005 (-0.09)	.003 (0.08)	-.014 (-0.37)	.013 (0.31)	.030 (0.69)	.022 (0.50)	.075 (1.57)
Fixed- short-term contract	.005 (0.07)	-.022 (-0.31)	-.066 (-1.17)	-.072 (-1.40)	-.041 (-0.78)	-.011 (-0.22)	-.002 (-0.03)	-.015 (-0.29)	.006 (0.07)
Other type of contract	-.133 (-0.88)	-.101 (-0.94)	-.167 (-1.27)	-.076 (-0.59)	-.062 (-0.66)	-.066 (-0.84)	-.167 (-2.46)	-.187 (-2.55)	-.162 (-1.72)
Firm size: 5-19 employees	.129 (2.54)	.072 (1.57)	.066 (1.65)	.055 (1.49)	.046 (1.31)	.053 (1.51)	.054 (1.43)	.047 (1.17)	.043 (0.99)
Firm size: 20-49 employees	.092 (1.64)	.100 (1.89)	.090 (1.99)	.108 (2.74)	.098 (2.50)	.099 (2.32)	.085 (1.82)	.069 (1.21)	.127 (2.58)
Firm size: 50-99 employees	.056 (0.82)	.105 (1.95)	.077 (1.73)	.117 (2.81)	.100 (2.58)	.095 (2.35)	.059 (1.30)	.067 (1.29)	.139 (2.35)
Firm size: 100-499 employees	.085 (1.42)	.054 (0.99)	.076 (1.56)	.063 (1.43)	.072 (1.56)	.061 (1.31)	.067 (1.50)	.067 (1.33)	.184 (2.39)
Firm size: more than 500 employees	.190 (3.18)	.147 (2.75)	.132 (2.91)	.141 (3.24)	.114 (2.70)	.114 (2.18)	.114 (2.19)	.186 (3.01)	.295 (3.67)
North-west	.008 (0.16)	.084 (2.08)	.064 (1.72)	.040 (1.08)	.036 (0.97)	.064 (1.55)	.095 (2.05)	.089 (1.67)	.155 (2.80)
North-east	.111 (2.26)	.080 (2.20)	.040 (1.04)	.026 (0.71)	.040 (1.14)	.039 (1.19)	.046 (1.19)	.048 (1.10)	.057 (1.19)
South and Islands	-.016 (-0.43)	-0.14 (-0.37)	-.005 (0.14)	-.009 (-0.31)	-.007 (-0.22)	.006 (0.17)	.040 (1.23)	.020 (0.64)	.017 (0.38)
Constant	1.874 (10.94)	1.958 (13.24)	2.141 (16.39)	2.174 (17.12)	2.236 (26.03)	2.266 (25.02)	.2.318 (20.93)	2.370 (20.35)	2.340 (16.49)
R^2	.378	.335	.319	.322	.328	.349	.377	.410	.437
Observations					831				

t-values in brackets.

Table A2b. Quantile regressions. Highly-educated men

	10th	20th	30th	40th	50th	60th	70th	80th	90th
Married/cohabitating	-.047 (-1.03)	.024 (0.70)	.0416 (1.41)	.056 (1.91)	.055 (1.72)	.058 (2.11)	.052 (1.68)	.065 (1.87)	.071 (1.46)
University education	.128 (3.25)	.127 (3.02)	.192 (4.75)	.185 (4.62)	.224 (4.64)	.271 (5.90)	.265 (5.55)	.241 (4.38)	.271 (4.24)
Experience	.018 (2.51)	.014 (2.37)	.013 (2.56)	.013 (2.60)	.016 (2.98)	.012 (2.33)	.011 (1.86)	.013 (1.80)	.011 (1.40)
Experience squared	-.000 (-1.56)	-.000 (-1.41)	-.000 (-1.23)	-.000 (-1.09)	-.000 (-1.81)	-.000 (-1.23)	-.000 (-1.03)	-.000 (-0.85)	-.000 (-0.50)
Experience*Children	.004 (2.74)	.002 (1.89)	.002 (1.48)	-.000 (-0.05)	.000 (0.16)	.000 (0.11)	-.000 (-0.58)	-.001 (-.046)	.000 (0.20)
Intermediate supervisory level	.082 (2.04)	.114 (3.11)	.104 (3.18)	.080 (2.90)	.078 (3.11)	.0999 (3.71)	.102 (3.61)	.090 (3.12)	.097 (2.41)
HIgh supervisory level	.165 (3.22)	.171 (4.00)	.186 (5.28)	.170 (4.94)	.185 (4.99)	.219 (5.70)	.235 (5.34)	.284 (4.30)	.361 (4.14)
Tenure 6-10 years	.108 (2.18)	.098 (2.37)	.076 (2.04)	.072 (2.08)	.031 (0.99)	.047 (1.38)	.022 (0.64)	.018 (0.42)	.042 (0.73)
Tenure 11-15 years	.155 (2.31)	.108 (2.10)	.086 (1.86)	.093 (2.19)	.038 (0.91)	.065 (1.69)	.071 (1.58)	.053 (0.93)	.076 (1.20)
Tenure more than 15 years	.160 (3.01)	.138 (3.41)	.109 (2.46)	.100 (2.52)	.076 (2.05)	.101 (2.82)	.089 (2.16)	.053 (1.08)	.112 (1.92)
Public sector	.060 (1.61)	.070 (2.03)	.082 (2.83)	.051 (1.87)	.071 (2.55)	.046 (1.63)	.0399 (1.36)	.036 (1.02)	.021 (0.50)
Agriculture	-.200 (-1.65)	-.236 (-2.23)	-.264 (-2.56)	-.268 (-2.77)	-.237 (-2.25)	-.208 (-2.04)	-.202 (-1.96)	-.100 (-0.81)	-.126 (-1.04)
Services	-.034 (-0.95)	.001 (0.03)	-.023 (-0.62)	-.012 (-0.44)	-.002 (-0.09)	.017 (0.72)	.016 (0.52)	.050 (1.41)	.063 (1.19)
Fixed- short-term contract	-.047 (-0.64)	-.048 (-0.83)	-.039 (-0.73)	-.069 (-1.43)	-.096 (-1.60)	-.095 (-1.30)	-.037 (-0.48)	-.004 (-0.04)	.042 (0.58)
Other type of contract	.072 (0.92)	.066 (0.67)	.044 (0.37)	.068 (0.48)	.097 (0.60)	.225 (1.51)	.199 (1.05)	.223 (1.05)	.556 (2.44)
Firm size: 5-19 employees	.023 (0.37)	.026 (0.56)	-.010 (-0.24)	-.002 (-0.07)	.015 (0.52)	.027 (0.86)	.034 (0.76)	.027 (0.42)	-.005 (-0.08)
Firm size: 20-49 employees	.015 (0.24)	.047 (0.96)	.008 (0.18)	-.008 (-0.21)	.020 (0.52)	.042 (1.07)	.057 (1.18)	.064 (1.02)	-.009 (-0.13)
Firm size: 50-99 employees	.071 (0.96)	.134 (2.53)	.059 (1.13)	.055 (1.20)	.076 (1.75)	.101 (2.31)	.119 (2.14)	.088 (1.28)	.051 (0.72)
Firm size: 100-499 employees	.081 (1.18)	.085 (1.59)	.048 (1.01)	.037 (0.93)	.033 (0.92)	.059 (1.39)	.083 (1.40)	.059 (0.79)	.034 (0.43)
Firm size: more than 500 employees	.065 (0.92)	.072 (1.35)	.021 (0.41)	.020 (0.46)	0.37 (0.99)	.054 (1.20)	.082 (1.49)	.033 (0.47)	.008 (0.11)
North-west	-.048 (-0.94)	.028 (0.52)	.013 (0.30)	.032 (0.97)	.021 (0.58)	.031 (0.90)	.016 (0.44)	.015 (0.33)	.018 (0.30)
North-east	.008 (0.17)	.073 (1.74)	.047 (1.36)	.032 (0.95)	.002 (0.07)	.012 (0.36)	.001 (0.03)	.000 (0.01)	.014 (0.19)
South and Islands	-0.83 (-2.64)	-.077 (-2.78)	-.098 (-3.55)	-.091 (-3.19)	-.085 (-2.66)	-.084 (-3.08)	-.066 (-2.38)	-.068 (-2.15)	-.020 (-0.50)
Constant	2.122 (12.08)	2.199 (24.83)	2.285 (33.44)	2.318 (36.18)	2.322 (34.65)	2.359 (35.91)	2.363 (27.61)	0.540 (24.23)	2.517 (29.39)
R^2	.313	.304	.309	.318	.329	.353	.380	.412	.453
Observations					1044				

t-values in brackets.

Table A3a. Quantile regressions. Low educated women

	10th	20th	30th	40th	50th	60th	70th	80th	90th
Married/cohabitating	.053	.018	.030	-.016	-.032	-.038	-.047	-.013	-.052
	(1.08)	(0.37)	(0.62)	(-0.35)	(-0.68)	(-0.82)	(-0.93)	(-0.27)	(-1.00)
Experience	.010	.016	.014	.009	.010	.009	.005	.002	.005
	(1.01)	(1.82)	(1.73)	(1.02)	(1.05)	(0.86)	(0.45)	(0.15)	(0.44)
Experience squared	-.000	-.000	-.000	-.000	-.000	-.000	-.000	-.000	-.000
	(-1.04)	(-1.67)	(-1.53)	(-0.82)	(-0.96)	(-0.84)	(-0.47)	(-0.26)	(-0.39)
Experience*Children	.001	-.002	-.002	.000	-.001	-.001	.001	-.001	-.004
	(0.29)	(-0.78)	(-0.83)	(0.11)	(-0.36)	(-0.51)	(0.45)	(-0.26)	(-1.18)
Intermediate supervisory level	-.005	.047	.012	.029	.062	.032	.014	.026	.129
	(-0.06)	(0.65)	(0.16)	(0.39)	(0.80)	(0.39)	(0.18)	(0.33)	(1.33)
High supervisory level	-.023	.030	.103	.105	.078	.071	.146	.208	.236
	(-0.15)	(0.20)	(0.67)	(0.72)	(0.59)	(0.49)	(0.99)	(1.50)	(1.93)
Tenure 6-10 years	.085	.038	.038	.000	.002	.031	.035	.028	-.084
	(1.00)	(0.60)	(0.60)	(0.01)	(0.05)	(0.50)	(0.52)	(0.44)	(-1.17)
Tenure 11-15 years	-.009	.010	-.014	-.005	.041	.044	.003	.007	-.041
	(-0.10)	(0.16)	(-0.22)	(-0.09)	(0.65)	(0.65)	(0.04)	(0.10)	(-0.48)
Tenure more than 15 years	-.033	-.035	.030	.057	.064	.080	.101	.154	.082
	(-0.38)	(-0.50)	(0.44)	(0.93)	(1.20)	(1.26)	(1.37)	(2.07)	(1.00)
Public sector	.141	.089	.091	.042	.073	.079	-.024	-.072	-.099
	(2.28)	(1.44)	(1.54)	(0.70)	(1.34)	(1.28)	(-0.38)	(-1.04)	(-1.26)
Agriculture	-.171	-.217	-.253	-.261	-.135	-.061	-.053	-.021	.131
	(-0.74)	(-0.98)	(-1.17)	(-1.19)	(-0.63)	(-0.29)	(-0.24)	(-0.09)	(0.57)
Services	.052	-.013	-.058	.009	.023	.012	.075	.062	.067
	(0.53)	(-0.14)	(-0.66)	(0.10)	(0.25)	(0.16)	(1.06)	(0.84)	(0.68)
Fixed- short-term contract	.118	.011	.026	.018	.003	-.002	.006	-.030	-.023
	(1.46)	(0.16)	(0.40)	(0.29)	(0.05)	(-0.03)	(0.08)	(-0.41)	(-0.29)
Other type of contract	-.369	-.332	-.241	-.257	-.147	-.071	-.048	-.056	-.168
	(-2.46)	(-2.04)	(-1.55)	(-1.66)	(-1.01)	(-0.57)	(-0.47)	(-0.64)	(-2.05)
Firm size: 5-19 employees	.065	.048	.049	.053	.065	.101	.100	.067	.059
	(0.67)	(0.71)	(0.95)	(1.17)	(1.51)	(2.14)	(1.89)	(1.21)	(0.91)
Firm size: 20-49 employees	.086	.070	.037	.071	.122	.139	.134	.089	.059
	(0.75)	(0.82)	(0.56)	(1.07)	(1.84)	(2.18)	(1.92)	(1.31)	(0.82)
Firm size: 50-99 employees	.065	.115	.018	.119	.118	.137	.101	.117	.167
	(0.56)	(1.25)	(0.25)	(1.68)	(1.73)	(1.75)	(1.17)	(1.23)	(1.67)
Firm size: 100-499 employees	.170	.204	.135	.152	.158	.276	.312	.323	.271
	(1.53)	(1.97)	(1.52)	(1.59)	(1.89)	(2.86)	(3.46)	(3.95)	(3.08)
Firm size: more than 500 employees	-.054	.044	-.003	.081	.146	.174	.235	.104	.135
	(-0.38)	(0.38)	(-0.03)	(0.74)	(1.41)	(1.67)	(2.03)	(0.82)	(0.94)
North-west	.144	.013	.040	.038	.071	.096	.076	.089	.072
	(1.47)	(0.16)	(0.57)	(0.60)	(1.11)	(1.52)	(1.30)	(1.28)	(1.05)
North-east	.127	.037	.024	.017	-.030	-.004	.024	.099	.145
	(1.99)	(0.64)	(0.40)	(0.28)	(-0.45)	(-0.06)	(0.37)	(1.59)	(2.27)
South and Islands	-.229	-.278	-.253	-.141	-.115	-.144	-.107	-.057	-.009
	(-2.53)	(-3.55)	(-3.37)	(-2.05)	(-1.98)	(-2.35)	(-1.49)	(-0.78)	(-0.12)
Constant	2.044	2.230	2.319	2.33	2.346	2.370	2.423	2.495	2.579
	(13.71)	(17.66)	(17.41)	(17.29)	(17.33)	(19.74)	(20.80)	(21.30)	(18.60)
R^2	.446	.343	.285	.252	.236	.235	.240	.269	.330
Observations					288				

t-values in brackets.

Table A3b. Quantile regressions. Low educated men

	10th	20th	30th	40th	50th	60th	70th	80th	90th
Married/cohabitating	.045 (1.04)	.068 (1.85)	.079 (2.49)	.080 (2.80)	.069 (2.38)	.058 (2.00)	.065 (2.57)	.072 (2.70)	.080 (2.13)
Experience	.025 (2.96)	.017 (2.54)	.010 (1.80)	.006 (1.28)	.006 (1.32)	.004 (0.91)	.001 (0.17)	-.002 (-0.42)	-.006 (-0.94)
Experience squared	-.000 (-2.50)	-.000 (-2.45)	-.000 (-1.67)	-.000 (-1.05)	-.000 (-0.92)	-.000 (-0.19)	.000 (0.24)	.000 (0.73)	.000 (1.26)
Experience*Children	.005 (0.39)	-.000 (-0.04)	-.000 (-0.03)	.001 (1.04)	.001 (1.45)	.001 (1.43)	.001 (1.26)	.002 (2.03)	.004 (2.49)
Intermediate supervisory level	.063 (1.05)	.075 (1.36)	.134 (3.14)	.096 (3.02)	.097 (3.67)	.073 (2.62)	.055 (1.87)	.046 (1.33)	0.38 (0.76)
HIgh supervisory level	-.020 (-0.24)	.044 (0.58)	.057 (0.76)	.037 (0.46)	.124 (1.63)	.128 (1.94)	.139 (2.27)	.141 (2.25)	.131 (1.85)
Tenure 6-10 years	-.004 (-0.08)	.032 (0.68)	.011 (0.30)	.013 (0.41)	.033 (1.00)	.026 (0.70)	.018 (0.48)	.005 (0.12)	.032 (0.63)
Tenure 11-15 years	.004 (0.07)	-.054 (-1.07)	-.009 (-0.18)	.013 (0.31)	.018 (0.56)	.012 (0.34)	-.014 (-0.45)	-.016 (-0.41)	.037 (0.55)
Tenure more than 15 years	.061 (1.26)	.064 (1.84)	.075 (2.15)	.084 (2.65)	.093 (3.27)	.071 (2.13)	.053 (1.48)	.075 (2.23)	.046 (0.98)
Public sector	.120 (1.93)	.124 (2.83)	.090 (2.43)	.045 (1.32)	.042 (1.34)	.053 (1.53)	.074 (1.95)	.054 (1.41)	.028 (0.56)
Agriculture	.095 (0.50)	.059 (0.55)	.001 (0.01)	.090 (1.14)	.036 (0.52)	-.001 (-0.02)	.053 (0.71)	.030 (0.45)	.051 (0.48)
Services	-.001 (-0.01)	-.005 (-0.11)	.035 (0.94)	.047 (1.33)	.069 (2.00)	.065 (2.04)	.051 (1.72)	.051 (1.49)	.029 (0.69)
Fixed- short-term contract	-.121 (-1.12)	-.073 (-0.85)	-.071 (-1.05)	-.069 (-1.27)	-.065 (-1.17)	-.020 (-0.35)	-.026 (-0.49)	-.042 (-0.84)	-.066 (-1.17)
Other type of contract	-.319 (-2.87)	-.306 (-3.94)	-.254 (-4.04)	-.246 (-3.98)	-.219 (-3.91)	-.157 (-3.75)	-.212 (-5.73)	-.214 (-5.44)	-.247 (-4.03)
Firm size: 5-19 employees	.015 (0.29)	.077 (1.86)	.067 (2.01)	.114 (3.46)	.089 (2.55)	.077 (2.46)	.0311 (0.95)	.032 (1.03)	.009 (0.28)
Firm size: 20-49 employees	-.026 (-0.37)	.052 (1.02)	.050 (1.05)	.100 (2.70)	.073 (2.23)	.059 (1.72)	.010 (0.28)	.010 (0.28)	-.035 (-0.69)
Firm size: 50-99 employees	.066 (1.08)	.117 (2.76)	.119 (3.06)	.127 (3.36)	.100 (2.72)	.084 (2.00)	.041 (0.84)	.006 (0.11)	.074 (1.12)
Firm size: 100-499 employees	.116 (1.82)	.136 (2.96)	.138 (3.44)	.155 (4.13)	.125 (3.52)	.152 (4.15)	.106 (2.67)	.105 (2.53)	.070 (1.52)
Firm size: more than 500 employees	.109 (1.52)	.160 (3.03)	.152 (3.14)	.205 (4.41)	.169 (3.73)	.151 (3.29)	.129 (2.60)	.123 (2.45)	.142 (2.34)
North-west	-.003 (-0.04)	.045 (0.75)	.152 (3.14)	.043 (1.15)	.028 (0.80)	.035 (0.82)	.039 (0.73)	.077 (0.93)	.097 (0.54)
North-east	.086 (1.72)	.053 (1.33)	.052 (1.28)	.038 (1.01)	.046 (1.24)	.052 (1.27)	.046 (1.12)	.042 (1.06)	.052 (0.95)
South and Islands	-.091 (-2.43)	-.050 (-1.57)	.042 (1.09)	-.013 (-0.52)	-.006 (-0.25)	-.021 (-1.05)	-.034 (-1.89)	-.048 (-2.08)	-.047 (-1.33)
Constant	1.904 (19.35)	2.067 (22.91)	-.026 (-0.96)	2.192 (41.80)	2.30 (38.49)	2.325 (37.30)	2.48 (36.38)	2.579 (36.32)	2.667 (33.20)
R^2	.286	.229	.219	.209	.201	.205	.202	.201	.207
Observations					742				

t-values in brackets.

Table A4. Tests on the hypothesis of equality between decile human capital-related coefficients. F-values (Prob>F)§

	Highly-educated		Low-educated	
	Women	Men	Women	Men
Couples of deciles				
10th-20th	.98 (.45)	.64 (.76)	.59 (.78)	1.03 (.41)
10th-30th	1.96 (.04)*	1.35 (.21)	.82 (.58)	1.17 (.31)
10th-40th	2.46 (.01)*	1.46 (.16)	1.06 (.39)	1.04 (.40)
10th-50th	1.95 (.04)*	1.88 (.05)*	1.03 (.42)	1.14 (.33)
10th-60th	1.92 (.05)*	2.33 (.01)*	.82 (.59)	1.16 (.32)
10th-70th	2.42 (.01)*	2.54 (.01)*	.96 (.46)	1.49 (.16)
10th-80th	2.61 (.00)*	2.17 (.02)*	1.80 (.08)*	1.55 (.14)
10th-90th	2.34 (.01)*	1.91(.05)*	1.90 (.06)*	1.81 (.07)*
20th-30th	.87 (.55)	.72 (.69)	.54 (.83)	1.69 (.10)*
20th-40th	1.26 (.25)	.95 (.48)	.99 (.45)	1.19 (.30)
20th-50th	.97 (.47)	1.12 (.35)	.72 (.67)	1.13 (.33)
20th-60th	.80 (.62)	1.91 (.05)*	.50 (.86)	1.36 (.21)
20th-70th	1.15 (.32)	2.08 (.03)*	.70 (.69)	1.24 (.27)
20th-80th	1.73 (.08)*	1.95 (.04)*	1.18 (.31)	1.25 (.26)
20th-90th	2.06 (.03)*	1.69 (.09)*	1.41 (.19)	1.51 (.15)
30th-40th	.62 (.78)	.94 (.50)	.84 (.56)	.57 (.80)
30th-50th	.52 (.86)	.82 (.60)	.54 (.82)	.63 (.75)
30th-60th	.49 (.88)	1.12 (.34)	.21 (.98)	1.07 (.38)
30th-70th	.77 (.65)	1.42 (.17)	.32 (.95)	1.49 (.16)
30th-80th	1.38 (.19)	1.08 (.37)*	.57 (.56)	1.68 (.10)*
30th-90th	2.14 (.02)*	1.25 (.37)	.85 (.56)	1.52 (.15)
40th-50th	.35 (.96)	1.53 (.13)	.43 (.90)	.69 (.70)
40th-60th	.75 (.66)	1.97 (.04)*	.21 (.99)	1.15 (.33)
40th-70th	.91 (.51)	1.83 (.06)*	.08 (.99)	1.19 (.30)
40th-80th	1.66 (.09)*	1.03 (.41)	.40 (.92)	1.15 (.33)
40th-90th	2.12 (.02)*	1.31 (.23)	.78 (.62)	1.06 (.39)
50th-60th	.82 (.60)	.85 (.57)	.13 (.99)	.63 (.75)
50th-70th	1.01 (.43)	.66 (.74)	.41 (.91)	1.16 (.32)
50th-80th	1.89 (.05)*	.55 (.83)	.72 (.67)	.83 (.58)
50th-90th	1.45 (.16)	.88 (.55)	.79 (.61)	1.06 (.39)
60th-70th	.63 (.77)	.47 (.89)	.64 (.74)	1.12 (.35)
60th-80th	1.11 (.35)	.49 (.88)	.66 (.72)	.78 (.62)
60th-90th	1.10 (.36)	.51 (.87)	1.04 (.41)	.73 (.66)
70th-80th	.87 (.55)	.43 (.92)	.70 (.69)	.39 (.93)
70th-90th	1.08 (.38)	.45 (.90)	1.17 (.32)	.53 (.83)
80th-90th	.83 (.59)	.58 (.81)	.68 (.71)	.72 (.68)

§ *We carry out the test on the whole set of human capital variables: education, experience, experience*children, tenure, supervisory level. The null hypothesis* $H_0 : b_i = b_j$ *is tested against the alternative hypotheses* $H_1 : b_i \neq b_j$ *−where* b_i *is the vector of i-th decile coefficients related to human capital characteristics. We identify with * F-tests that are significant at least at 10%.*

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