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Understanding the gender wage-gap differential between the public and private sectors in Italy: A quantile approach☆

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ABSTRACT

This paper analyzes the gender-based wage gaps across the wage distribution in the private and public sectors in Italy for the years 2005–2010. We use quantile regression methods to estimate and decompose the wage gap at all wage levels and propose a two-step procedure that relies on a novel approach to estimating fixed effects quantile regressions. The method's main advantage is that it allows the employment sector's marginal effect on wages at various points of the distribution to be estimated, while accounting for both observable and time-invariant unobservable factors. The new method stresses important differences with respect to standard decomposition analyses and amplifies the differences in the two sectors' wage-setting mechanisms. When the estimation is net of individual heterogeneity, the gender-based wage gap decreases in both sectors and there is evidence of a *glass ceiling* effect, but only in the public sector. Economic grounds are provided.

1. Introduction

Gender-based differences in the labor market's wages have seen considerable attention from policy-makers and researchers, leading to the implementation of equal-pay legislation and the promotion of equal opportunity. Even though these policies have been promoted in Western industrialized countries for several decades, differences in pay based on gender persist, and there are tremendous differences across countries. A robust finding in the literature is that the difference in pay based on gender cannot be entirely explained by differences in human capital or job or firm characteristics and that the unexplained part of the gap is large. Moreover, recent research has shown that the magnitude of the gender wage gap (GWG) varies substantially across both the public and the private sector at all wage levels.

The theoretical interpretations of differences in the GWG between the two sectors include that, as Gregory and Borland (1999), among others, argue, these differences in wage structure are not surprising given that wage-setting in the public sector occurs in a political environment, whereas private-sector decision-making occurs in a market environment. It is entirely possible that greater attention to bureaucratic procedures for wage-setting and pay comparability in the public sector can lead to better relative wage outcomes for women than is likely in the private sector. Moreover, anti-discrimination legislation may be more aggressively enforced in the public sector, and there is some evidence that occupational integration has been more rapid in public-sector employment. Public-sector jobs also tend to be concentrated in larger establishments, in a limited number of industries, and in some occupations that employ particularly well-educated workers. Finally, public-sector employment may attract more risk-averse workers (Pfeifer, 2008).

The empirical evidence on how the relative wages of men and women vary across sectors shows that the mean GWG is typically considerably smaller in public-sector jobs than in private-sector jobs (Arulamplam et al., 2007; Gregory and Borland, 1999; Gunderson, 1989), while the distribution of wages varies dramatically between sectors (Arulamplam et al., 2007; Kee, 2006). However, the finding of a smaller GWG in the public sector is limited to developed economies only, as Lausev (2014) and Ganguli and Terrell (2005) stress.

Barón and Cobb-Clark (2010) investigate the GWG across the public and private sector at all wage levels for Australia. They find that

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the GWG among high-wage workers is largely unexplained in both the private and public sectors, while is more than explained by differences in individual characteristics among low-paid workers. This finding suggests that *glass ceilings*, rather than *sticky floors*, may be prevalent in explaining the GWG in the two sectors. For *glass ceilings* and *sticky floors* we refer to the unexplained component of the GWG's widening at the top and at the bottom of the wage distribution.

The results of Barón and Cobb-Clark (2010) are confirmed by the Blau and Kahn (2003)'s analysis, who find that, on average, employers' wage decisions and the difference between men's and women's wage increases over their work lives discriminate based on gender. Further, the unexplained gender gap in the public sector increases with the wage level and with respect to the private sector.

Arulamplam et al. (2007) investigate GWG by sector for eleven European countries and conclude that glass ceilings are more prevalent than sticky floors in most countries. The authors show that the magnitude of the GWG varies substantially across the public and private sectors' wage distributions. The main finding in Kee (2006) for Australia is that a strong glass ceiling effect is detected only in the private sector. On the other hand, Wahlberg (2010) provides evidence of a glass ceiling effect in both the private and public sectors (particularly in the public sector) for the Swedish market.

Miller (2009) extends Arulamplam et al. (2007) and Kee's (2006) line of inquiry to the US labor market. Miller's analysis shows that the GWG differs by sector of employment and based on the part of the earnings distribution that is considered. The pay differential in the US's private sector does not show either the glass ceiling or sticky floor effects that are reported for many other countries. However, the government sector is characterized by a distinct sticky-floor effect in the difference between women's and men's pay.

Zweimüller and Winter-Ebmer (1994) draw attention to the role of job level on the GWG in Austria, identifying a discriminatory promotion scheme and showing structural differences between the two sectors: women are over-represented at the bottom of the job hierarchy in the private sector, while they are under-represented from middle management positions upward in the public sector. Chatterjia et al. (2011) investigate the role of workplace characteristics in explaining the gender earnings gap in the public and private sectors in Britain. Even including detailed workplace characteristics does little to explain the GWG in both sectors.

Rahona-López et al. (2016) show a consistent level of GWG in Spain and that the wage differences are significantly greater in the private sector across all wage levels. Moreover, while women have better human capital endowments than men in the public sector, men have better human capital endowments in the private sector. The empirical evidence shows also that the GWG is more pronounced at the top of the earnings distribution and that the GWG cannot be explained by differences in productive characteristics, with differences in returns accounting for 80 percent or more of the observed gap between the best-paid workers in the public and private sectors.

However, the results change when the analysis is pointed to transitioning countries in Eastern Europe, as shown by, for instance, Ganguli and Terrell (2005), Pignatti (2012), and Lausev (2014). Ganguli and Terrell (2005) examine gender gaps across all wage levels in Ukraine after Ukraine began to be considered a market economy. Ganguli and Terrell find evidence in both sectors of a persistent *glass ceiling*-but lower in the public sector than in the private sector-effect. By decomposing the GWG into its components, they find differences in men's and women's (observed) productive characteristics that favor men in the public sector and women in the private sector. However, they report substantial evidence in each year and in each sector that the most important force in driving the gender gaps throughout the wage distribution are differential rewards-that is, wage discrimination. They confirm Pignatti's (2012) analysis of the effect of gender-equalizing policies on reducing the GWG, particularly at the bottom of the distribution. Ganguli and Terrell (2005) show that the GWG in the private sector is smaller than that in the public sector at the top half of the distribution, a result that is confirmed by Lausev (2014), who shows that the lower GWG in the public sector is limited only to developed economies, while in the transitioning countries of Eastern Europe, for example, the GWG in the public sector is wider than that in the private sector.

This paper presents an analysis of the GWG in Italy in the public and private sectors and a decomposition of its determinants. For this task we rely on Machado and Mata's (2005) methodology to obtain counterfactual distributions of the wage gap.

Machado and Mata's (2005) procedure is extensively applied in the context of both the estimation of GWG, as in Albrecht et al. (2003), Arulamplam et al. (2007), and Albrecht et al. (2009), and that of the wage differential in general (Arabsheibani et al., 2018). However, in addition to using Machado and Mata's (2005) approach, we consider the unobserved individual-specific heterogeneity by means of the quantile regression for panel data that Canay (2011) proposes. To determine how the GWG varies across wage levels we propose a two-step procedure to compute the Oaxaca-Blinder decomposition: First we estimate the GWG using Canay's (2011) approach and then we run the Machado and Mata's (2005) decomposition for quantile regression. The main advantage of our method is that it allows the employment sector's marginal effect on wages at various points of the distribution to be estimated while accounting for both observable and time-invariant unobservable factors.

The results of the analysis conducted with standard techniques are in line with those of Barón and Cobb-Clark (2010) and Blau and Kahn (2003). We find a lower but still significant GWG in the public sector with respect to the private one, and the GWG increases along the wage distribution in both sectors. The Oaxaca-Blinder decomposition shows that the unexplained component usually exceeds the explained part, and the distance grows as the wage increases. This pattern is much more evident in the public sector, where we find evidence of a *glass ceiling* mechanism in action. In the private sector the proportion of the GWG that cannot be explained by observable characteristics is higher at the bottom of the distribution (i.e., *sticky floor*).

However, when we take into account the unobserved individual heterogeneity, the results of the analysis change. The evidence of a sticky floor in the private sector vanishes while the evidence of glass ceiling in the public sector increases. However, the GWG in both sectors has a significant unexplained component throughout the distribution.

The paper is organized as follows. Section 2 presents the econometric approach, while Section 3 describes the data. Section 4 reports and discusses the results on the GWG in each sector based on a cross-section analysis. Section 5 extends the analysis to take into account the individual heterogeneity in the longitudinal sample. Finally, Section 6 concludes.

2. Econometric modelling and methodology

We estimate the wage equations by means of quantile regression, as developed by Koenker and Bassett (1978). Following Buchinsky (1998) and assuming a linear specification, the model is defined as

$$Q_\theta(y_i \mid x_i) = x_i' \beta_\theta \tag{1}$$

$$y_i = x_i' \beta_\theta + u_{\theta i} \tag{2}$$

where $Q_\theta(y_i \mid x_i)$ defines the *conditional quantiles* of the dependent variable y (log wages), given the covariates x (individual characteristics). The distribution of the error term $u_{\theta i}$ is left unspecified and it is assumed that $Q_\theta(u_{\theta i} \mid x_i) = 0$.

To investigate the gender wage gap in the public sector, we estimate this model for men and women separately at different quantiles, namely $\theta = \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Results based on quantile regressions provide a complete view of how the wage gaps between and within sectors varies along the distribution. Moreover, as the quantile regression (QR) allows the regressors, i.e. individual observable characteristics, to have a different impact at different quantiles, we can control more deeply for differences between men and women's wages that depend on their characteristics.

2.1. Quantile decomposition

To decompose the wage gap in explained and unexplained components, we make use of the procedure proposed by Machado and Mata (2005), that generalizes the Oaxaca-Blinder decomposition to a quantile regression framework. The advantage of the quantile decomposition is that we can estimate the unexplained component of the wage gap across the distribution of wage, that is, at any quantile of the wage distribution.

While in the Oaxaca-Blinder setting, the wage gap is divided by means of a *counterfactual wage structure*, the Machado and Mata's (2005) decomposition is based on the construction of a counterfactual distribution of y^f, i.e. a distribution of what would be female wage, had the wage structure been the same as the male one.

Let $k \in \{m, f\}$ represent male and female observations, so that we have samples $\left\{(y_i^k, x_i^k) : i = 1, \dots, n_k\right\}$ for all populations k, and we can estimate $Q_\theta(y^k)$ separately for the two groups.

Formally, the Machado-Mata approach to estimate the counterfactual distribution of y^f can be summarized as follows[1]:

1. Draw a random sample θ_i^*, $i = 1, 2, \dots, 5000$ from a uniform distribution $U[0, 1]$.
2. For each θ_i, estimate $\beta^m(\theta)$ and $\beta^f(\theta)$ as

$$\hat{\beta}^k(\theta_i^*) = \arg\min_{\beta \in \mathbb{R}^p} \sum_{j=1}^{n_k} \rho_{\theta_i^*}(y_j^k - x_j'^k \beta) \quad k = m, f.$$

using the male and female dataset, respectively.[2]

3. Randomly draw 5,000 women with replacement and use their characteristics (x^{*f}) to predict the wages using the estimated coefficients $\beta^m(\theta)$ generating a set of predicted wages, $\tilde{y}^f(\theta) = x'^{*f}\hat{\beta}^m(\theta)$. The empirical c.d.f. of these values is the estimated counterfactual distribution, namely what women would have earned if they were paid like men.
4. Then compare the counterfactual distribution with the empirical male and female distributions whose θquantiles are defined by $\hat{y}^m(\theta) = x'^m\beta^m(\theta)$ and $\hat{y}^f(\theta) = x'^f\beta^f(\theta)$, respectively.

As in the Oaxaca-Blinder decomposition for the mean differential, the wage gap between males and females can be divided in two parts; one representing the effect of different characteristics between the two groups; the other representing differences unexplained by the quantile regression model. The advantage of the quantile decomposition is that we can estimate the two components across the distribution of wage, that is, at any θth quantile of the wage distribution.

More precisely, we can write

$$y^m(\theta) - y^f(\theta) = [\hat{y}^m(\theta) - \tilde{y}^f(\theta)] + [\tilde{y}^f(\theta) - \hat{y}^f(\theta)] + residual \tag{3}$$

where $y^k(\theta)$ denotes the observed log wages for $k = (male, female)$, $\hat{y}^k(\theta)$ denotes the estimator of the $k = (male, female)$ log wages based on the observed sample, and $\tilde{y}^f(\theta)$ denotes the estimated counterfactual log wages. By *counterfactual*, we mean the wage that females would get, if their abilities had been rewarded according to the male pays' schedule.[3]

The first part of the wage differential is the so-called *characteristics* effect, since it is the consequence of the different distribution of covariates for the two groups. The second addend in (3) represents the *effect of the wage structure*, since it is obtained by evaluating female characteristics using two different conditional distributions. As the same endowments should have the same effect on earnings for male and female, the wage structure should not differ by gender, which is why this term represents the unexplained part of the GPG.

In the following analysis we make use of the estimation procedure for standard errors proposed by Chernozhukov et al. (2013). In fact, Machado and Mata (2005) proposed quantile regression-based estimators to evaluate distributional effects, but provided no econometric theory for these estimators. The asymptotic behavior of the estimators' error is studied by Chernozhukov et al. (2013) who also show the validity of *exchangeable bootstrap* methods to obtain the asymptotic covariance matrix.

2.2. Quantile regression for panel

To take into account the unobserved individual heterogeneity in explaining the GWG, we extend our empirical analysis by exploiting the longitudinal structure of the data.[4] To this end, we consider the following quantile regression fixed effect model (FE-QR hereafter):

$$Q_\theta(y_{it} \mid x_{it}) = \alpha_i + x_{it}'\beta_\theta \tag{4}$$

$$y_{it} = x_{it}'\beta_\theta + u_{\theta it} \tag{5}$$

While estimation methods for cross-sectional conditional quantile regression models are well developed, corresponding methods for panel data (especially FE models) have received attention only recently. The FE-QR is designed to control for individual-specific heterogeneity while exploring heterogeneous covariate effects, so it provides a more flexible method for analyzing panel data than that afforded by the mean regression models.

One problem associated with FE-QR is that the method of differencing out the fixed effects used for the conditional linear mean model does not carry over to the conditional quantiles. Koenker (2004) proposes treating each individual effect as a parameter to estimate[5] by means of a penalized estimation method. However, controlling fixed effects by directly estimating them is not without difficulty because of the incidental parameter problem (Neyman and Scott, 1948), which manifests in inconsistency in the common parameters when the number of individuals goes to infinity and the time period is fixed.[6]

A second problem arises because the objective function cannot be differentiated. The implication is that standard asymptotic analysis of panel data model is not directly applicable to QR. Kato and Galvao (2016) propose smoothing the objective function and study the estimator's properties, showing that the estimator is asymptotically normally distributed and proposing a bias correction for the estimator's mean. Flores et al. (2014) estimate a two-way fixed effects model

[1] The decomposition proposed by Machado and Mata (2005) grounds on the probability integral transformation theorem from elementary statistics: if U is uniformly distributed on $[0, 1]$, then $F^{-1}(U)$ has distribution F. Thus, for a given x_i and a random $\theta \sim U[0, 1]$, $x_i'\beta(\theta)$ has the same distribution as $y_i \mid x_i$. If, instead of keeping x_i fixed, we draw a random x from the population, $x'\beta(\theta)$ has the same distribution of y.

[2] As shown by Koenker and Bassett (1978), the quantile estimator of β_θ solves the following minimization problem.

$$\hat{\beta}(\theta) = \arg\min_{\beta \in \mathbb{R}^p} [\sum_{j: y_j \geq x_j'\beta} \theta|y_j - x_j'\beta| + \sum_{j: y_j < x_j'\beta} (1-\theta)|y_j - x_j'\beta|]$$

[3] The residual term captures the changes unaccounted for by the estimation method, and in general it is considered negligible.

[4] See Section 3 for the characteristics of the data when we rely on panel observations.

[5] The individual fixed effects are treated as pure location-shift parameters that are common to all conditional quantiles.

[6] Graham et al. (2009) and Kato and Galvao (2016) describe the analysis of an incidental parameter problem in FE-QR.

where both effects vary over quantiles. Flores et al. (2014) account for the problem of *quantile crossing*, adopting the method Chernozhukov et al. (2010) propose to transform the original estimated quantiles into monotonic ones. However, the objective function they consider is not smooth, and they rely on a Monte Carlo experiment to show the small bias in their estimates. Harding and Lamarche (2014) introduce alternative approaches that do not consider the case of unobserved heterogeneity represented by the classical individual effects, proposing a quantile regression estimator for a model with a multifactor error structure and interactive effects that may be correlated with covariates.

In our application we follow the approach Canay (2011) proposes. In line with Koenker (2004), Canay (2011) assumes a pure location shift effect for the individual parameters, that is, that the fixed effects affect all quantiles in the same way. Canay (2011) proposes an easy-to-use two-step estimator that first estimates the individual effects α_i by traditional mean estimations (e.g., estimation in first differences or by means of the within estimator) before estimating corrected wages, $\hat{y}_{it} = y_{it} - \hat{\alpha}_i$, on the other covariates by means of traditional quantile regression. Given $\hat{y}_{it}$, we estimate the wages by quantile regression and rely on Machado-Mata method to decompose the wage gap in observed and unobserved components.

We adopt the FE-QR estimator Canay (2011) proposes because it does not add computational complexity to the model estimation. In fact, estimations and inferences that use alternative FE-QR may be difficult to conduct when the number of FE is large. In addition, inference using FE-QR is difficult to conduct in practice. When the number of FE is large, point estimates are difficult to recover, and the computation of the variance-covariance matrix based on the limiting distribution becomes impracticable. We rely on the good finite-sample properties of the estimator Canay (2011) provides, even for low values of T. To run the decomposition of the GWG across sectors in Section 5, we proceed as follows. First, we estimate, for each sector, two fixed effects models for the sample of men and the sample of women:

$$y_{it}^{f} = \alpha_i^{f} + x_{it}^{f\prime}\beta^{f} + \epsilon_{it,f} \tag{6}$$

$$y_{it}^{m} = \alpha_i^{m} + x_{it}^{m\prime}\beta^{m} + \epsilon_{it,m} \tag{7}$$

where f (m) stands for female (male) employee.

Second, we estimate

$$Q_\theta(\hat{y}_{it}^{f} \mid x_{it}) = x_{it}^{f\prime}\beta_\theta^{f} \tag{8}$$

$$Q_\theta(\hat{y}_{it}^{m} \mid x_{it}) = x_{it}^{m\prime}\beta_\theta^{m} \tag{9}$$

where $\hat{y}_{it}^{k} = y_{it}^{k} - \hat{\alpha}_i^{k}$ for ($k = f, m$) is the log wage, net of the estimated individual heterogeneity. Third, we apply the Machado-Mata decomposition to compute the counterfactual distribution of $\hat{y}$ and to obtain the decomposition in equation (3).

3. Data and preliminary analysis

To carry out our analysis, we rely on individual data drawn from the 2005, 2006, 2008, and 2010 waves of the ISFOL-PLUS survey. ISFOL is the Italian Institute for the Development of Vocational Training for Workers. The data were collected in the context of a joint project with the Italian Ministry of Labor and Social Policy that was started in 2005.[7] The project seeks to create a data set for the study of wage inequality by gender, so it delivers broad information on personal work profiles, individual motivations to work, and the participants' cultural and territorial backgrounds.

Since the first PLUS survey in 2005, each year has included panel interviews with participants from the previous sample. We consider the panel dimension in our analysis, taking into account all available years. The target population is composed of individuals between the ages of fifteen and sixty-four. ISFOL chose stratified sampling with optimal allocation over five types of domains: region, size of the municipality, gender, age, and occupational status. A multi-domain inclusion strategy was implemented to guarantee a sampling error below a given threshold and a significant sampling size for each domain. One of the main characteristics of the national survey is that only answers with direct responses were considered, that is, no proxies were used.

The ISFOL-PLUS questionnaire is composed of sections for five subgroups of the population: people between ages fifteen and twenty-nine; women between ages twenty and forty-nine; people between ages fifty and sixty-four, unemployed people, and employed people. A rich set of information for each of these categories is included, ranging from family characteristics to individual skills and personal histories. Although the self-employed and those with project-linked positions are present in the PLUS samples, we consider only salaried employees, which form by far the largest category. Our analysis focuses on full-time employees between ages eighteen and sixty-four. Facing the usual trade-off between representativeness of the sample at the population level and the comparability across sectors, we opt in favor of the latter and make additional selections for the sake of comparability. We restrict the sample to people who work under a full-time, permanent contract and exclude trainees and those with temporary contracts. Part-time workers are excluded, as their pay dispersion is larger than that of their full-time colleagues, increasing the probability that they earn less than the average hourly wage. Moreover, the incidence of part-time work differs significantly between men and women, favoring women (e.g., Chzhen and Mumford, 2011).

We use the log of the hourly net wage (adjusted to the 2010 level) as the dependent variable. We determine each individual's hourly wage by dividing the reported monthly salary by the number of weeks worked in the month, multiplied by the number of hours usually worked during the week.[8] We use this measure rather than monthly or annual pay to rid our analysis of the effect of the different number of hours worked by men and women. Finally, we exclude blue-collar workers because they are strongly over-represented in the private sector (about 35%) compared to the public sector (about 10%) and would make the two distributions much less comparable in terms of occupation types and earnings. We select a group of about thirty independent variables, which include years of education, family characteristics (civil status, presence of pre-school-age children), occupation and industry dummies, geographic variables (denoting people living in northern and central regions and people living in urban areas), and such personal skills that may reveal individual ability as knowledge of English and knowledge about how to use a computer for particular basic tasks. In addition to these personal skills, we consider the *University Performance*, that is, the university degree score penalized for years lost.[9]

Table A.1 in the Appendix describes the variables we use for our descriptive analyses and in the decompositions. Table A2 presents descriptive statistics for male and female public- and private-sector

[7] The data was collected by means of Computer Assisted Telephone Interviewing (CATI).

[8] We use net hourly wage instead of gross hourly wage because of data limitations. The ISFOL-PLUS survey collects data on the net monthly wage for employees and on the gross monthly wage for those who are self-employed.

[9] The variable *University Performance* is a proxy for the unobserved ability of individuals who have a university degree. Proposed by Castagnetti and Rosti (2009), the variable is given by the final degree score, penalized by any excess in the number of years used to get the degree. For a complete definition of the variable, see Table A1 in Appendix A.

Fig. 1. Kernel-density estimates of hourly net log-wages by gender and sector.

employees in our sub-sample.[10]

The means of the variables considered show that, on average, men earn higher salaries in both sectors and have longer work histories and that public-sector employees are, on average, better educated than private-sector employees. On the other hand, women have more years of education and higher university performance. The number of years of education is constructed from the available information on educational attainment, so it has relatively low variability.

A first visual summary of the wage distribution across sectors, between genders, and within sectors is provided in Fig. 1. The density functions are estimated using the Epanechnikov kernel estimator.[11] Fig. 1 shows that, in both sectors, private and public, the women's wage distribution is shifted to the left of the men's wage distribution, which gives us a preliminary evidence of a GWG. However, at this preliminary stage, we consider only the unconditional wage distribution without taking into account the factors that may affect it.

The regression-based decompositions of Sections 4 and 5 are based on quantile estimation, the main strength of which lies in its allowing productivity and coefficients gender differentials to be estimated across the wage distribution. As a preliminary step in the investigation of the effects on the GWG of differences in individual characteristics, we carry out a series of quantile regressions on the pooled data. Pooled quantile regressions, shown in Tables A3 and A4, estimate the wage by sector, including (in addition to standard individual and work-related characteristics) a gender dummy to identify the GWG.

Each coefficient shown in the tables represents the effect on wages in a given quantile of a shift in the corresponding covariate, keeping all else constant. The standard errors are computed using the bootstrap method with 800 replications, a procedure that involves weaker assumptions with regard to the distributional form taken by the variables of interest, since it provides a consistent estimate even in the presence of heteroskedasticity.[12]

The GWG based on the parameter of the dummy variable *Female* when the homogeneity of parameters by gender is imposed, appears to be larger in the public sector. Additional evidence from this model is that the return on *University Performance* is higher in the public sector. On the other hand, the other variables for individual ability have more influence on wages in the private sector.

Finally, while the dummies that denote the presence of children is significant only for a small number of quantiles and mostly in the public sector, the variables that denote civil status are statistically significant in both sectors and across the whole distribution.

4. Cross-section decomposition

To decompose the differences in the wage distribution according to the Oaxaca-Blinder decomposition, we apply the Machado-Mata procedure described in Section 2.1. While the preliminary dummy-based approach presented in Section 3 has the important shortcoming of assuming that the return to individual and job characteristics is the same across genders, the Machado-Mata decomposition relies on the estimation of quantile wage regressions for both gender and sector. We estimate four specifications, denoted in Table A5's columns A-D. Specification A is an extended version of the Mincer equation that we augment sequentially with indicators of individual productivity and ability (specification B), with occupational dummy variables (specification C), and with dummies for industry classification (specification D). Tables A6–A9 present the estimation results at five quantiles of the wage distribution for specification D of Table A5.[13] These results allow us to evaluate the overall accuracy of our wage specifications, to test the significance of each of our proxies for productivity, and to appreciate any differences between the sectors and between the genders in terms of the shape taken by the wage structure.

The decomposition by sector of the GWG presented in Figs. 2–5 leads to several observations. First, in both sectors, the relative wages increase across the distribution, and the GWG in the private sector is always bigger than those in the public sector. The decomposition of the GWG shows that a significant part of the GWG remains unexplained in both sectors after controlling for individual characteristics, education, job attributes, and regional specific effects. Moreover, the weight of the unobserved component in explaining the GWG is always bigger in the public sector than it is in the private sector. We observe also that the effect of the wage structure decreases along the wage distribution for the private sector, while it increases for the public sector. Comparing the two sectors, we observe that, among high wage workers, the wage gap faced by women is completely unexplained in the public sector and mostly unexplained in the private sector. It also appears that high-wage public-sector employees in Italy face more employer discrimination[14] (i.e., glass ceilings) than low-wage workers do (i.e., sticky floors).[15]

This result contrasts with Melly's (2005) findings for Germany but confirms Barón and Cobb-Clark's 2010 findings. Further, Arulamplam et al. (2007) and Kee (2006) find no evidence of sticky floors in public-

[10] A comparison of our working sample to the initial sample shows that the two show very similar characteristics except for the education level. The exclusion of blue-collar workers from the sample increased the level of education and the *University performance* in both gender and sector. However, this upward change does not alter the relative education gap between those in the private and public sectors or between the genders.

[11] The bandwidth is chosen to minimize the mean integrated squared error, where the data are Gaussian and a Gaussian kernel is used. We adopt this criteria-that is, the default option in STATA-to minimize the degree of discretion in presenting the results.

[12] Two good, short reviews on inference methods for quantile regression are Buchinsky (1995) and Buchinsky (1998). For a more comprehensive treatment of the topic, see Koenker (2005).

[13] To save space we report only the detailed estimation results of specification D. The results of the remaining specifications are available on request.

[14] The literature on the GWG in general identifies the unexplained component of the GWG as the discrimination component. However, as Blau and Kahn (2006) and others stress, the unexplained portion of the GWG may include effects of unobserved productivity or compensating differentials.

[15] In particular, the part of GWG that is attributed to the wage structure goes from about 50% for the lowest quantiles to about 90% at the highest quantiles.

Fig. 2. Gender wage gap decomposition, divided by sector. Specification A in Table A5. 95% confidence intervals.

Fig. 3. Gender wage gap decomposition, divided by sector. Specification B in Table A5. 95% confidence intervals.

sector employment for Europe and Australia, respectively.

In the private sector, unlike the public sector, the unexplained component of the conditional GWG decreases along the wage distribution, so it seems that employer discrimination is more prevalent among low-wage employees than it is among their high-wage counterparts. Therefore, contrary to what we found for the public-sector, the mechanism in action seems to be of sticky floors, rather than glass ceilings. However, when we control for occupation and industry, the relative effect of the observed characteristics on the GWG increases only for the private sector. The change in the wage structure's contribution to the GWG goes in the same direction, decreasing for the private sector and comparatively stable for the public sector. One implication is an effect of gender segregation in the private sector, while no evidence of the same is found for the public sector.

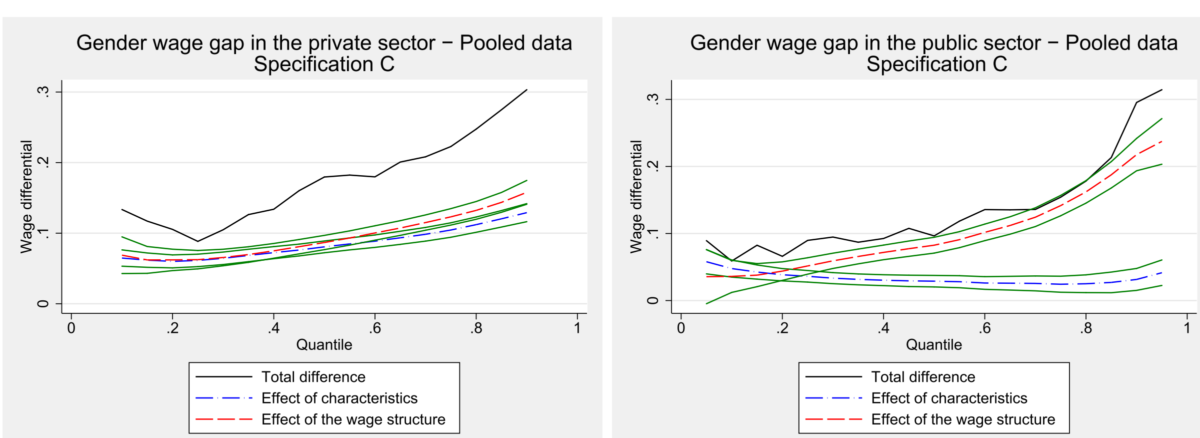

Fig. 4. Gender wage gap decomposition, divided by sector. Specification C in Table A5. 95% confidence intervals.

Fig. 5. Gender wage gap decomposition, divided by sector. Specification D in Table A5. 95% confidence intervals.

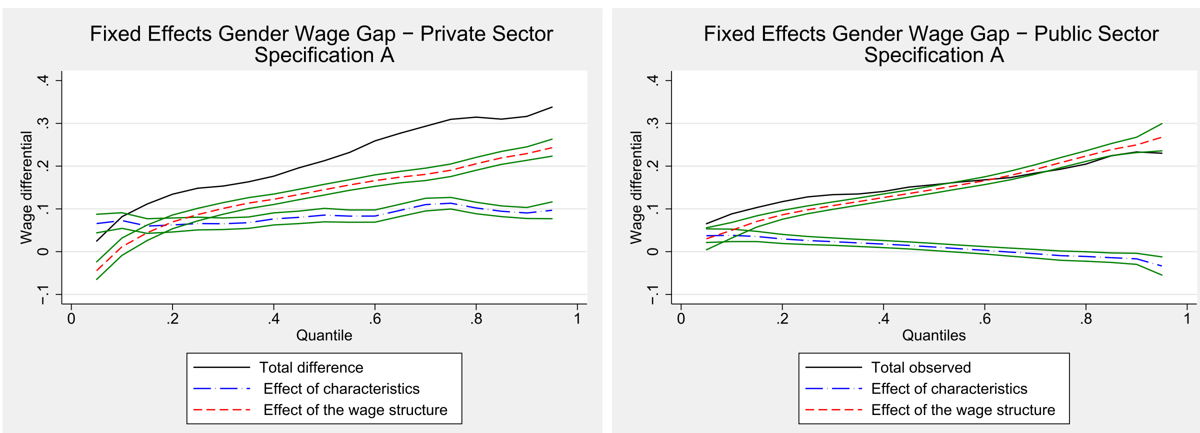

Fig. 6. Fixed effects gender wage gap by sector. Specification A in Table A5. 95% confidence intervals.

5. Longitudinal decomposition

The first step in the longitudinal analysis is the fixed effects estimation of the wage equation by gender and sector. The Machado-Mata decomposition is then applied on the wage netted from the estimated individual heterogeneity (Section 2). As for the cross-section analysis, we first estimate a model that excludes occupation, industry, and individual ability controls from the vector of labor market position variables (specification A). We then repeat the estimation/decomposition exercise, adding controls for measures of ability (specification B), for occupation (specification C), and for industry (specification D). Thus, we seek to identify the extent to which the results are driven by occupational and industrial segregation. In the spirit of Arulamplam et al. (2007) analysis, this procedure may also provide insights into the sensitivity of the unexplained component (i.e., the effect of the wage structure) to alternative assumptions about the discriminatory nature of the

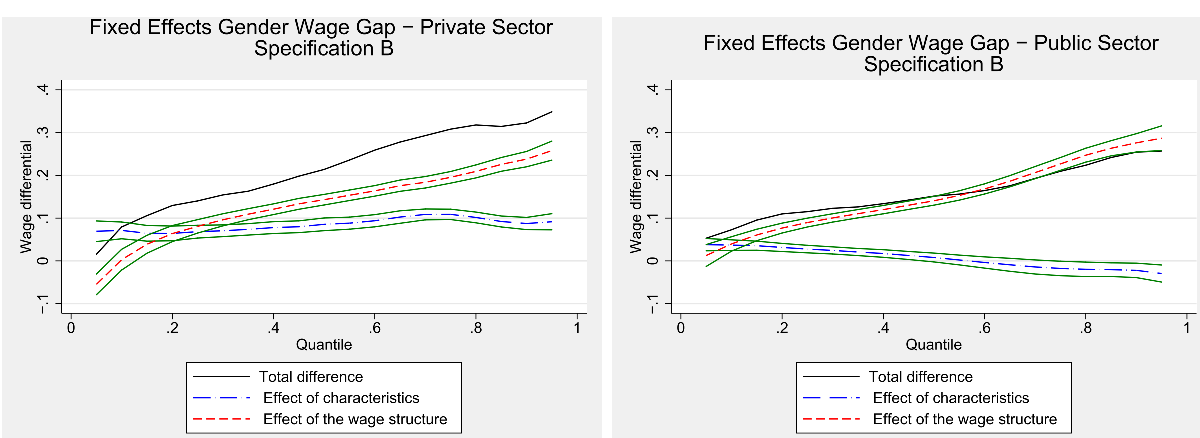

Fig. 7. Fixed effects gender wage gap by sector. Specification B in Table A5. 95% confidence intervals.

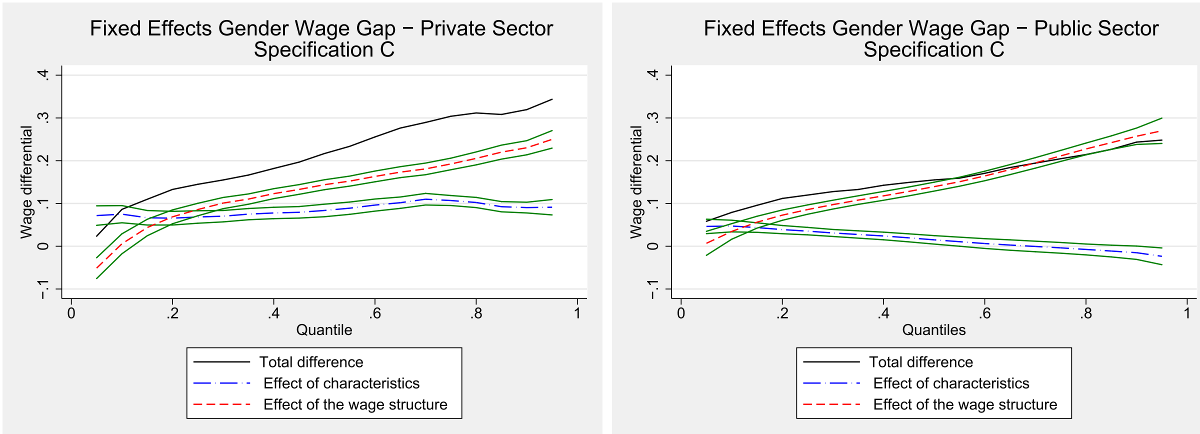

Fig. 8. Fixed effects gender wage gap by sector. Specification C in Table A5. 95% confidence intervals.

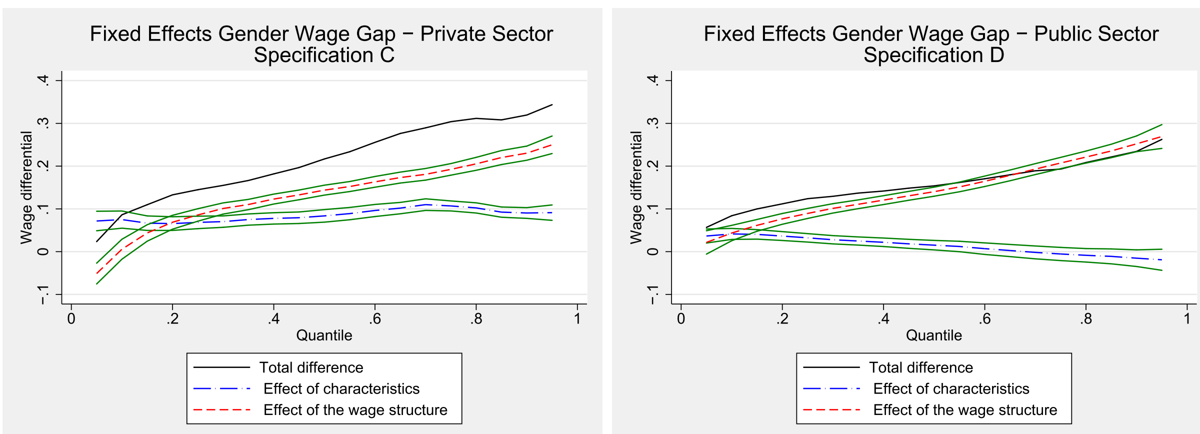

Fig. 9. Fixed effects gender wage gap by sector. Specification D in Table A5. 95% confidence intervals.

occupational distribution itself.

Tables A10–A13 show the estimation results at five quantiles of the *net wage*[16] distribution for Specification D of Table A5.[17] These results allow the overall accuracy of our wage specification to be evaluated, the significance of each of our proxies for productivity to be tested, and any differences in the shape taken by the wage structure between the sector and gender dimensions to be evaluated. At this stage, the comparison of the estimation results of Section 4 provides no evidence on important differences.

The decomposition analysis in Figs. 6–9 shows three primary differences with respect to the results presented in Section 4. First, in both sectors the GWG markedly declines when individual heterogeneity is taken into account. Second, the evidence of a glass ceiling in the public sector remains valid while the weight of the wage structure's effect on the GWG is comparatively stable across the distribution in the private sector. Third, in the public sector the gender difference in the observed characteristics is statistically significant only in the lower quantile of the distribution. Unlike the public sector, the private sector shows that these characteristics make a statistically significant contribution to the GWG's explanation throughout the wage distribution.

Moreover, the rate at which the GWG increases across the distribution is much lower in the public sector and much higher in the cross-section analysis. The control for individual heterogeneity has a weaker impact on the wage decomposition in the private sector than it does in the public sector. The level of the GWG in the public sector is lower across the distribution with respect to the cross-section analysis, but the evidence of a sticky floor in the private sector vanishes. Like the public sector, the decomposition results for the private sector show that the GWG rises as the wage level increases.

Important evidence arises from the minimal impact (on the decomposition between sectors) of introducing occupation and industry measures into the set of labor market controls. (See Figs. 6–9). Unlike the cross-section analysis, the longitudinal analysis does not provide evidence of a segregation effect. The percentage of the GWG that the observed and unobserved factors (i.e., the effect of characteristics and the wage structure effect) account for remains largely unchanged, so no information is gained from controlling for proxies of individual ability, occupation, and industry allocation. Thus, the effect of segregation that is highlighted in the cross-section analysis is only apparent; the individual heterogeneity explains much more.

When the estimation is net of the individual heterogeneity, the evidence that the magnitude (and source) of the GWG varies across the two sectors, supporting the view that the wage-setting mechanisms in the two sectors differ. One factor in explaining these differences is the hiring methods the two sectors use. In Italy public servants are usually recruited through public contests and open competition. These public contests increase the accuracy of assessment, as they require the use of objective criteria and justification of the candidate choice, thereby increasing the probability of fair assessment for both men and women over that of other recruitment methods. Dobbs and Crano (2001) argue

[16] $\hat{y}^k_{it}$ in (8) and (9).

[17] To save space, we report only the detailed estimation results of specification D. The results for the other specifications are available on request.

that individuals who have to justify their decisions have stronger incentives to bypass their stereotyped impressions than do those who do not. As a consequence, when decision-makers are required to justify their choices and describe the criteria they use to evaluate candidates, as they do in open competitions, they are unlikely to discriminate against any particular group. Therefore, the lower GWG in the public sector can be the result of both the different selection methods and the greater effort in the application of gender-equality policies.

The explanation for the larger unexplained component of the GWG in the public sector has two parts. At the bottom of the distribution, the unexplained component may cover non-monetary benefits offered by the public sector. At the top of the distribution, the increasing weight of the wage effect may hide *favoritism* in the public sector for men rather than discrimination against women. For example, the top management job positions in the public sector are often linked to the political appointments that tend to favor men over women.

6. Conclusion

The significant and persistent level of the GWG has garnered considerable attention from policy-makers and researchers, leading to the implementation of an equal-pay legislation and the promotion of equal opportunities in many countries. Beginning in 2008, the GWG has been among the indicators for monitoring occupation policies in the European Union. Despite efforts to combat the GWG,[18] women in Europe are paid an average of 16.30% less than men are paid. The GWG must be decomposed in terms of explained (observed) and unexplained (unobserved) components. In this paper, we investigate the decomposition by gender of the wages in Italy's public and private sectors. Using quantile regression methods, we perform the analysis for both cross-section and panel data. For the latter, we perform the analysis by considering the quantile approach for panel data that Canay (2011) proposes. To determine how the GWG varies across the wage distribution, we propose a two-step procedure for computing the Oaxaca-Blinder decomposition, first estimating the GWG using Canay's (2011) approach and then running the Machado-Mata decomposition for quantile regression.

Because of the more standardized career path in the public sector with respect to the private one and the different selection methods (by competition in the public sector), the unexplained component of the GWG, at least at the early career stages, should be lower in the public sector than it is in the private sector. Hence, we expect a larger unexplained component for the GWG in the private sector than in the public counterpart.

In line with findings in the extant literature, our main results confirm the substantially higher level of the GWG in the private sector with respect to the public sector. When we control for the unobserved individual heterogeneity, we find a consistent decrease in the GWG and in the slope of the wage curve in both sectors. The evidence of a sticky-floor effect in the private sector from the cross-section analysis vanishes, while the public sector still shows a glass-ceiling effect. However, both sectors have a significant unexplained GWG whose weight is larger in the public sector throughout the wage distribution.

Our explanation for these results suggests that the lower GWG in the public sector can be the result of the differing hiring-selection methods and of putting more effort into the application of policies for gender equality. The increasing weight of the wage effect (the unexplained component of the GWG) observed in the public sector at the top of the distribution may also hide *favoritism* for men, rather than discrimination against women. For example, the top management job positions in the public sector are often linked to political appointment that favor men over women. At the bottom of the distribution, the higher weight of the unexplained component of the GWG in the public sector may cover nonmonetary benefits offered by the public sector that, particularly in Italy, play an important role in the welfare system and wage-setting in the labor market.

Appendix A. Definition of variables

Table A1
Definition of variables.

Variable Name	Definition
Log net hourly wage	Natural logarithm of hourly wages in Euros net of taxes and social security contributions
Female	One if the individual is woman, zero otherwise
Experience	Number of years of work experience
Experience^2	*Experience* squared
Tenure	Number of years worked for current employer
Schooling	Number of years of schooling completed
University_Degree	One if the individual has graduated from university, zero otherwise
University Performance	$\frac{DegreeScore}{1+0.1*Years}$ where *Degree Score* is the degree mark plus the laude or highest honors when it occurs. *Years* is the number of years in excess used to get the degree. In the Italian education system, each faculty only sets a minimum number of years in which to obtain a degree. As a consequence there is a high dispersion in the age at which students graduate. The speed of completion of the academic career is, therefore, together with the final mark, an important component of educational performance. The degree scores have been normalized to take into account the different marking scale for each faculty. The final degree score ranges from 66 to 110 (for some universities the maximum mark awarded is 100). According to each faculty internal ruling a laude (distinction) may be assigned to candidates with a 110/110 mark for recognition of the excellence of their thesis (in the analysis the 110 cum laude is considered as 111).
High School	One if highest education was high school, zero otherwise
Secondary Education	One if highest degree obtained was secondary education, zero otherwise
Primary Education	One if highest education obtained was primary education, zero otherwise
Knowledge of English	One if the individual answer "yes" to all the questions of PLUS questionnaire on the ability to speak and understand English, zero otherwise
Computer skill	One if the individual answer "yes" to all the questions of PLUS questionnaire on the ability to using PC, zero otherwise
North	One if the individual lives and works in the North of Italy, zero otherwise
Centre	One if the individual lives and works in the Centre of Italy, zero otherwise
Age	Age of the individual (in years)
Married	One if the individual is married, zero otherwise

(*continued on next page*)

[18] The European Commission is adopting an Action Plan to defeat the GWG over the next biennium.

Table A1 *(continued)*

Variable Name	Definition
Kids	One if the individual has at least one child, zero otherwise
Kids_10	One if the age of the youngest child is below 10 years, zero otherwise In the wave of 2005, *Kids_10* is equal to one if there is at least one child below the age of three in the household, zero otherwise
Italian	One if the individual holds the Italian citizenship, zero otherwise
Mother's university degree	One if the mother's education is equal to *University_Degree*, i.e. the mother holds a university degree, zero otherwise
Father's university degree	One if the father's education is equal to *University_Degree*, i.e. the father holds a university degree, zero otherwise
Metropolitan Area	One if individual is located in a metropolitan area, zero otherwise
Permanent Contract	One if the individual holds an unlimited contract, zero otherwise
Manager	One if the respective individual is occupied in an intellectual profession; scientific or highly specialized occupations, zero otherwise
Intermediate_Profession	One if the respective individual is occupied in an intermediary position in the commercial, technical or administrative sector, in health services or is a technician, zero otherwise
White − collars worker	One if the respective individual is occupied in an intermediary position in the commercial, technical or administrative sector, in health services or is a technician, zero otherwise
Agriculture	One if the individual is engaged in agriculture, hunting and fishing, zero otherwise
Manufacturing	One if the individual is engaged in manufacturing, zero otherwise
Energy	One if the individual is engaged in energy, zero otherwise
Construction	One if the individual is engaged in construction, zero otherwise
Retail	One if the individual is engaged in retail and wholesale, zero otherwise
Tourism	One if the individual is engaged in tourism, zero otherwise
Transport	One if the individual is engaged in transport, warehousing and logistic, zero otherwise
Finance	One if the individual is engaged in finance and insurance services, zero otherwise
Health	One if the individual is engaged in health and care, zero otherwise
Telecommunication	One if the individual is engaged in telecommunication, zero otherwise
Government Administration	One if the individual is engaged in government administration, zero otherwise
Education	One if the individual is engaged in education, zero otherwise
AdminServices	One if the individual is engaged in administrative services, zero otherwise
Other Services	One if the individual is engaged in other firms and business services, zero otherwise
Public_Sector	One if individual is employed in the public sector, zero otherwise
Large Firm	One if firm has at least 10,000 workers, zero otherwise
Year_1 − Year_3	Year dummies, one if year = 2005, 2006, 2008, respectively, and zero otherwise

Appendix B. Descriptive statistics and estimation results

Table A2
Descriptive statistics.

Variable	Private		Public	
	Mean	Std. Dev.	Mean	Std. Dev.
Net hourly wage	1.948	0.433	2.182	0.365
Net hourly wage - women	1.848	0.391	2.108	0.321
Net hourly wage - men	2.037	0.449	2.248	0.389
Female	0.468	0.499	0.473	0.499
Age	36.867	12.589	46.010	11.697
Age - women	34.072	11.210	44.149	11.571
Age - men	39.322	13.208	47.680	11.558
Married	0.455	0.498	0.690	0.462
Kids	0.587	0.492	0.724	0.447
Kids_10	0.098	0.298	0.089	0.285
Mother's university degree	0.043	0.204	0.038	0.191
Father's university degree	0.061	0.239	0.084	0.278
Experience	15.471	12.453	23.905	11.581
Experience - women	12.609	11.000	21.720	11.743
Experience - men	17.988	13.097	25.868	11.072
Monthly hours worked	180.982	23.572	168.756	22.983
Permanent contracts	0.521	0.500	0.523	0.500
Tenure	10.231	10.601	18.995	11.489
Large Firm	0.424	0.494	0.468	0.499
North	0.554	0.497	0.385	0.487
Centre	0.190	0.392	0.198	0.399
Metropolitan area	0.321	0.467	0.348	0.476
Education				
Schooling	13.573	2.806	14.276	3.021
University degree	0.240	0.427	0.371	0.483
University degree - women	0.250	0.433	0.418	0.493
University degree - men	0.231	0.422	0.328	0.469
University performance	90.650	15.364	92.880	16.241
University performance - women	93.194	12.163	94.805	12.348
University performance - men	89.786	13.306	93.134	12.874
High School	0.643	0.479	0.528	0.499
Secondary Education	0.111	0.314	0.097	0.296
Primary Education	0.006	0.076	0.005	0.067
Knowledge of English	0.432	0.495	0.286	0.452
Computer skill	0.914	0.280	0.869	0.338

(*continued on next page*)

Table A2 *(continued)*

Variable	Private		Public	
	Mean	Std. Dev.	Mean	Std. Dev.
Occupation				
Managers	0.143	0.350	0.286	0.452
Intermediate professions	0.209	0.406	0.227	0.419
White-collars workers	0.648	0.478	0.487	0.500
Sector				
Agriculture	0.010	0.101	0.007	0.084
Manufacturing	0.098	0.297	0.005	0.073
Energy	0.058	0.234	0.009	0.095
Construction	0.023	0.150	0.005	0.068
Retail	0.117	0.321	0.011	0.105
Tourism	0.044	0.204	0.007	0.081
Transport	0.122	0.327	0.023	0.150
Finance	0.084	0.278	0.020	0.140
Health	0.029	0.168	0.132	0.339
Telecommunication	0.097	0.296	0.024	0.152
Government Administration	0.052	0.222	0.255	0.436
Education	0.041	0.198	0.246	0.431
AdminServices	0.059	0.236	0.122	0.327
Other Services	0.165	0.371	0.135	0.342
No of observations	14439		9957	

See Appendix A for the definition of the variables.

Table A3
Quantile regression of wage in the private sector.

	q10	q25	q50	q75	q90
Schooling	0.0193***	0.0170***	0.0195***	0.0199***	0.0212***
	(0.0025)	(0.0025)	(0.0021)	(0.0019)	(0.0025)
Experience	0.0341***	0.0234***	0.0212***	0.0203***	0.0205***
	(0.0022)	(0.0012)	(0.0010)	(0.0012)	(0.0020)
Experience2	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Female	−0.075***	−0.076***	−0.085***	−0.112***	−0.131***
	(0.0063)	(0.0063)	(0.0036)	(0.0062)	(0.0064)
Agriculture	−0.042	−0.078	−0.075***	−0.094**	−0.106***
	(0.0662)	(0.0583)	(0.0232)	(0.0416)	(0.0383)
Manufacturing	−0.012	−0.015	−0.026**	−0.060***	−0.068***
	(0.0265)	(0.0113)	(0.0131)	(0.0145)	(0.0226)
Energy	0.0011	0.0036	−0.025**	−0.060***	−0.079***
	(0.0288)	(0.0101)	(0.0119)	(0.0182)	(0.0152)
Construction	−0.077	−0.021	0.0030	−0.038***	−0.069**
	(0.0603)	(0.0220)	(0.0167)	(0.0132)	(0.0302)
Retail	−0.031	−0.029***	−0.046***	−0.087***	−0.106***
	(0.0274)	(0.0079)	(0.0092)	(0.0121)	(0.0174)
Tourism	−0.034	−0.067***	−0.061***	−0.081***	−0.073***
	(0.0341)	(0.0196)	(0.0113)	(0.0149)	(0.0267)
Transport	−0.026	−0.048***	−0.045***	−0.076***	−0.078***
	(0.0170)	(0.0143)	(0.0096)	(0.0149)	(0.0205)
Finance	0.0251	0.0134	0.0043	0.0048	−0.005
	(0.0178)	(0.0094)	(0.0106)	(0.0138)	(0.0205)
Health	−0.085**	−0.062*	−0.058***	−0.051*	−0.066
	(0.0338)	(0.0375)	(0.0208)	(0.0272)	(0.0493)
Telecommunication	0.0027	0.0146	−0.000	−0.006	−0.008
	(0.0344)	(0.0138)	(0.0093)	(0.0119)	(0.0188)
Government Administration	−0.046	−0.011	−0.011	−0.039**	−0.061***
	(0.0473)	(0.0232)	(0.0161)	(0.0167)	(0.0141)
Education	0.0285***	−0.020*	−0.030**	−0.061***	−0.077**
	(0.0092)	(0.0119)	(0.0141)	(0.0178)	(0.0319)
AdminServices	−0.068**	−0.055***	−0.048***	−0.070***	−0.092***
	(0.0322)	(0.0141)	(0.0180)	(0.0125)	(0.0200)
Permanent Contract	0.0252*	0.0069	0.0126***	−0.006	−0.013
	(0.0137)	(0.0061)	(0.0043)	(0.0091)	(0.0136)
Large firm	0.1051***	0.0770***	0.0710***	0.0595***	0.0538***
	(0.0149)	(0.0088)	(0.0054)	(0.0080)	(0.0083)
Manager	−0.031	0.0497***	0.0713***	0.1036***	0.1483***
	(0.0199)	(0.0123)	(0.0076)	(0.0079)	(0.0129)

(*continued on next page*)

Table A3 *(continued)*

	q10	q25	q50	q75	q90
Intermediate Profession	0.0180	0.0158	0.0203**	0.0248**	0.0508**
	(0.0143)	(0.0110)	(0.0097)	(0.0120)	(0.0203)
Married	0.0657***	0.0574***	0.0758***	0.0823***	0.0799***
	(0.0100)	(0.0101)	(0.0058)	(0.0087)	(0.0116)
Kids	0.0041	0.0073	0.0133**	0.0101*	0.0133
	(0.0123)	(0.0074)	(0.0063)	(0.0061)	(0.0120)
Kids_10	0.0206	0.0115	0.0089	0.0161	0.0170
	(0.0145)	(0.0104)	(0.0107)	(0.0155)	(0.0206)
University Performance	0.0004	0.0005***	0.0005***	0.0007***	0.0008***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Knowledge of English	−0.004	0.0170**	0.0247***	0.0231***	0.0345***
	(0.0141)	(0.0085)	(0.0060)	(0.0085)	(0.0094)
Computer skill	0.0976***	0.0903***	0.0892***	0.0864***	0.0777***
	(0.0186)	(0.0100)	(0.0100)	(0.0152)	(0.0143)
University degree father	−0.034	−0.007	0.0234***	0.0408**	0.0853***
	(0.0395)	(0.0144)	(0.0082)	(0.0168)	(0.0218)
University degree mother	0.0749	0.0229**	−0.001	−0.004	−0.011
	(0.0555)	(0.0099)	(0.0124)	(0.0168)	(0.0207)
Metropolitan area	−0.023***	−0.002	0.0066	−0.002	−0.009
	(0.0062)	(0.0072)	(0.0062)	(0.0063)	(0.0106)
North	0.1727***	0.0930***	0.0547***	0.0560***	0.0476***
	(0.0165)	(0.0064)	(0.0063)	(0.0099)	(0.0107)
Centre	0.1409***	0.0749***	0.0350***	0.0304**	0.0476***
	(0.0224)	(0.0073)	(0.0078)	(0.0121)	(0.0143)
Time effects	X	X	X	X	X
Constant	0.6759***	1.0980***	1.2632***	1.4512***	1.5884***
	(0.0435)	(0.0316)	(0.0297)	(0.0324)	(0.0311)
Number of observations	14439				
Pseudo R^2	0.1576	0.1547	0.2083	0.2458	0.2668

Bootstrap s.e. in parenthesis (800 replications). ***: significant at.99 level; **: significant at.95 level; *: significant at.90 level.

Table A4
Quantile regression of wage in the public sector.

	q10	q25	q50	q75	q90
Schooling	0.0139***	0.0138***	0.0154***	0.0172***	0.0203***
	(0.0021)	(0.0006)	(0.0014)	(0.0012)	(0.0021)
Experience	0.0329***	0.0247***	0.0202***	0.0213***	0.0232***
	(0.0020)	(0.0015)	(0.0012)	(0.0011)	(0.0019)
Experience2	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Female	−0.059***	−0.071***	−0.095***	−0.138***	−0.158***
	(0.0069)	(0.0048)	(0.0062)	(0.0063)	(0.0120)
Agriculture	−0.023	−0.078**	−0.102***	−0.126**	−0.045
	(0.0257)	(0.0388)	(0.0272)	(0.0583)	(0.0421)
Manufacturing	−0.049	0.0253	0.0009	−0.058*	−0.107
	(0.0705)	(0.0396)	(0.0507)	(0.0300)	(0.0716)
Energy	0.0075	0.0142	−0.015	−0.027	−0.125*
	(0.0740)	(0.0282)	(0.0135)	(0.0214)	(0.0698)
Construction	−0.064	−0.008	−0.015	−0.018	−0.015
	(0.0764)	(0.0344)	(0.0279)	(0.0596)	(0.0445)
Retail	−0.196**	−0.089***	−0.089***	−0.122***	−0.094**
	(0.0982)	(0.0266)	(0.0194)	(0.0227)	(0.0421)
Tourism	−0.025	−0.007	−0.052*	−0.067*	−0.083**
	(0.0593)	(0.0339)	(0.0284)	(0.0373)	(0.0336)
Transport	−0.022	0.0145	0.0007	0.0438*	0.0194
	(0.0348)	(0.0203)	(0.0163)	(0.0252)	(0.0312)
Finance	−0.024	0.0034	−0.035	−0.041	−0.056
	(0.0596)	(0.0265)	(0.0255)	(0.0297)	(0.0366)
Health	−0.041*	−0.036**	−0.054***	−0.057***	−0.092***
	(0.0217)	(0.0145)	(0.0126)	(0.0171)	(0.0160)
Telecommunication	0.0032	−0.009	0.0135	0.0109	−0.022
	(0.0476)	(0.0214)	(0.0277)	(0.0281)	(0.0378)
Government Administration	−0.019*	−0.014	−0.027***	−0.042***	−0.062***
	(0.0098)	(0.0105)	(0.0102)	(0.0140)	(0.0088)
Education	−0.016	−0.014**	−0.024***	−0.022*	−0.030***
	(0.0125)	(0.0060)	(0.0090)	(0.0116)	(0.0115)
AdminServices	0.0087	0.0248**	0.0314**	0.0517***	0.0064
	(0.0162)	(0.0102)	(0.0144)	(0.0191)	(0.0210)
Permanent Contract	0.0221**	0.0025	0.0164	0.0107	0.0080
	(0.0097)	(0.0106)	(0.0133)	(0.0095)	(0.0196)

(*continued on next page*)

Table A4 *(continued)*

	q10	q25	q50	q75	q90
Large firm	0.0168	0.0090	0.0261	0.0425**	0.0486
	(0.0166)	(0.0172)	(0.0182)	(0.0183)	(0.0336)
Manager	0.0101	0.0670***	0.1143***	0.2001***	0.2746***
	(0.0148)	(0.0121)	(0.0089)	(0.0157)	(0.0219)
Intermediate Profession	0.0139	0.0455***	0.0597***	0.0520***	0.0509***
	(0.0095)	(0.0078)	(0.0085)	(0.0093)	(0.0105)
Married	0.0400**	0.0259***	0.0289***	0.0325***	0.0302*
	(0.0180)	(0.0092)	(0.0097)	(0.0076)	(0.0156)
Kids	0.0205**	0.0155**	0.0123**	0.0179**	0.0132
	(0.0095)	(0.0066)	(0.0060)	(0.0088)	(0.0123)
Kids_10	0.0351**	0.0300***	0.0328***	0.0229	0.0138
	(0.0143)	(0.0100)	(0.0083)	(0.0146)	(0.0115)
University Performance	0.0006***	0.0007***	0.0010***	0.0016***	0.0019***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Knowledge of English	0.0059	0.0001	0.0077	0.0205***	0.0264***
	(0.0124)	(0.0080)	(0.0051)	(0.0066)	(0.0092)
Computer skill	0.0333***	0.0543***	0.0564***	0.0541***	0.0489***
	(0.0105)	(0.0065)	(0.0074)	(0.0063)	(0.0140)
University degree father	−0.001	−0.002	0.0305***	0.0400**	0.0334
	(0.0386)	(0.0147)	(0.0102)	(0.0192)	(0.0267)
University degree mother	−0.000	−0.024	−0.028	−0.007	0.0151
	(0.0287)	(0.0185)	(0.0222)	(0.0234)	(0.0350)
Metropolitan area	−0.003	−0.009	−0.011**	−0.012	−0.007
	(0.0137)	(0.0085)	(0.0055)	(0.0109)	(0.0129)
North	0.0067	−0.000	−0.001	0.0054	0.0130
	(0.0126)	(0.0055)	(0.0059)	(0.0064)	(0.0156)
Centre	0.0010	−0.004	−0.000	0.0148	0.0528***
	(0.0100)	(0.0097)	(0.0083)	(0.0097)	(0.0156)
Time effects	X	X	X	X	X
Constant	1.1657***	1.3861***	1.5238***	1.6053***	1.7006***
	(0.0373)	(0.0314)	(0.0252)	(0.0242)	(0.0485)
Number of observations	9957				
Pseudo R^2	0.1388	0.1425	0.1604	0.2167	0.2966

Bootstrap s.e. in parenthesis (800 replications). ***: significant at.99 level; **: significant at.95 level; *: significant at.90 level.

Table A5
Specification.

	A	B	C	D
Schooling	X	X	X	X
Experience	X	X	X	X
Experience^2	X	X	X	X
Permanent Contract	X	X	X	X
Large firm	X	X	X	X
Married	X	X	X	X
Kids	X	X	X	X
Kids_10	X	X	X	X
University degree father	X	X	X	X
University degree mother	X	X	X	X
Metropolitan area	X	X	X	X
North	X	X	X	X
Centre	X	X	X	X
Year dummies	X	X	X	X
Measures of individual ability[a]		X	X	X
Occupational dummies[b]			X	X
Sectors[c]				X

[a] University Performance, Knowledge of English, Computer skill.
[b] Manager and Intermediate Profession, White collar is the reference category.
[c] 13 Sectors, Other Services is the reference category. See Appendix A for the definition of the variables.

Table A6
Quantile regression of wage for males in private sector. Specification D.

	q10	q25	q50	q75	q90
Schooling	0.0184***	0.0168***	0.0210***	0.0210***	0.0223***
	(0.0037)	(0.0026)	(0.0019)	(0.0017)	(0.0031)
Experience	0.0351***	0.0250***	0.0237***	0.0256***	0.0237***
	(0.0044)	(0.0023)	(0.0016)	(0.0021)	(0.0022)
Experience^2	−0.0005***	−0.0003***	−0.0002***	−0.0002***	−0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agriculture	−0.0775	−0.1324	−0.1078***	−0.1025	−0.1757***
	(0.1034)	(0.0927)	(0.0394)	(0.0719)	(0.0532)
Manufacturing	−0.0298	−0.0204	−0.0305	−0.0638***	−0.0842***
	(0.0283)	(0.0284)	(0.0185)	(0.0220)	(0.0229)
Energy	0.0150	0.0221	−0.0166	−0.0441**	−0.0873***
	(0.0453)	(0.0195)	(0.0116)	(0.0213)	(0.0297)
Construction	−0.0838	−0.0145	−0.0136	−0.0706**	−0.1331***
	(0.0722)	(0.0346)	(0.0190)	(0.0299)	(0.0284)
Retail	0.0123	−0.0195	−0.0453**	−0.0692***	−0.0963**
	(0.0331)	(0.0258)	(0.0178)	(0.0266)	(0.0391)
Tourism	−0.0183	−0.0578**	−0.0499**	−0.0627*	−0.0223
	(0.0279)	(0.0268)	(0.0248)	(0.0324)	(0.0489)
Transport	−0.0201	−0.0448*	−0.0544***	−0.0724***	−0.0664**
	(0.0199)	(0.0240)	(0.0178)	(0.0158)	(0.0269)
Finance	0.0378	0.0212	−0.0067	−0.0169	−0.0691***
	(0.0262)	(0.0173)	(0.0145)	(0.0178)	(0.0161)
Health	−0.1126	−0.0323	−0.0541*	−0.0252	−0.0500
	(0.1085)	(0.0655)	(0.0282)	(0.0377)	(0.0431)
Telecommunication	−0.0165	0.0220	0.0013	−0.0211	−0.0213
	(0.0380)	(0.0295)	(0.0273)	(0.0261)	(0.0363)
Government Administration	0.0185	−0.0039	−0.0112	−0.0430	−0.0575
	(0.0570)	(0.0396)	(0.0242)	(0.0338)	(0.0413)
Education	0.0359	−0.0225	−0.0620*	−0.0624	−0.0534
	(0.0291)	(0.0247)	(0.0345)	(0.0401)	(0.0482)
AdminServices	−0.0485	−0.0578*	−0.0768**	−0.0858***	−0.0932**
	(0.0527)	(0.0343)	(0.0326)	(0.0313)	(0.0460)
Permanent Contract	0.0268	0.0084	0.0090	0.0033	−0.0324**
	(0.0193)	(0.0123)	(0.0097)	(0.0128)	(0.0155)
Large firm	0.0833***	0.0698***	0.0537***	0.0420***	0.0366**
	(0.0172)	(0.0111)	(0.0062)	(0.0068)	(0.0146)
Manager	0.0110	0.0651***	0.0766***	0.1026***	0.1736***
	(0.0448)	(0.0165)	(0.0148)	(0.0180)	(0.0320)
Intermediate Profession	−0.0046	0.0038	0.0095*	0.0224**	0.0517***
	(0.0225)	(0.0089)	(0.0048)	(0.0109)	(0.0191)
Married	0.0572**	0.0612***	0.1006***	0.1109***	0.1317***
	(0.0258)	(0.0128)	(0.0081)	(0.0205)	(0.0202)
Kids	0.0389**	0.0161	0.0138**	−0.0110	−0.0114
	(0.0153)	(0.0113)	(0.0056)	(0.0087)	(0.0138)
Kids_10	0.0134	0.0122	0.0221	0.0106	0.0153
	(0.0174)	(0.0198)	(0.0158)	(0.0171)	(0.0292)
University Performance	0.0004**	0.0006***	0.0006***	0.0008***	0.0007***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Knowledge of English	−0.0235	0.0154**	0.0224***	0.0249***	0.0360***
	(0.0153)	(0.0069)	(0.0079)	(0.0093)	(0.0127)
Computer skill	0.0668	0.0628***	0.0835***	0.1013***	0.0816***
	(0.0423)	(0.0167)	(0.0120)	(0.0215)	(0.0201)
University degree father	0.0112	0.0258	0.0408**	0.0653***	0.1069***
	(0.0439)	(0.0200)	(0.0191)	(0.0228)	(0.0349)
University degree mother	−0.0119	0.0062	−0.0225	−0.0242*	−0.0460
	(0.0657)	(0.0198)	(0.0159)	(0.0134)	(0.0293)
Metropolitan area	0.0085	0.0077	0.0016	−0.0099	−0.0233
	(0.0213)	(0.0090)	(0.0046)	(0.0085)	(0.0171)
North	0.1443***	0.0746***	0.0544***	0.0582***	0.0623***
	(0.0273)	(0.0127)	(0.0096)	(0.0088)	(0.0168)
Centre	0.1104***	0.0462**	0.0164	0.0190	0.0520*
	(0.0384)	(0.0209)	(0.0173)	(0.0193)	(0.0298)
Constant	0.7310***	1.1074***	1.2423***	1.3734***	1.5490***
	(0.0664)	(0.0214)	(0.0367)	(0.0366)	(0.0768)
Time effects	X	X	X	X	X
Number of observations	7685				
Pseudo R^2	0.1388	0.1425	0.1604	0.2167	0.2966

Bootstrap s.e. in parenthesis (800 replications). ***: significant at.99 level; **: significant at.95 level; *: significant at.90 level.

Table A7
Quantile regression of wage for females in private sector. Specification D.

	q10	q25	q50	q75	q90
Schooling	0.0251***	0.0178***	0.0151***	0.0158***	0.0216***
	(0.0058)	(0.0027)	(0.0018)	(0.0028)	(0.0033)
Experience	0.0310***	0.0220***	0.0186***	0.0166***	0.0177***
	(0.0035)	(0.0014)	(0.0017)	(0.0013)	(0.0012)
Experience^2	−0.0004***	−0.0003***	−0.0002***	−0.0001***	−0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agriculture	−0.0796	−0.0284	−0.0589	−0.0563	−0.1027***
	(0.1319)	(0.0963)	(0.0585)	(0.0573)	(0.0260)
Manufacturing	−0.0034	−0.0155	−0.0328	−0.0617***	−0.0639*
	(0.0334)	(0.0203)	(0.0245)	(0.0099)	(0.0333)
Energy	−0.0614**	−0.0377*	−0.0554***	−0.0735***	−0.1041**
	(0.0265)	(0.0226)	(0.0179)	(0.0194)	(0.0463)
Construction	−0.0720	−0.0393	0.0326	0.0117	−0.0051
	(0.1075)	(0.0410)	(0.0364)	(0.0394)	(0.0334)
Retail	−0.0866***	−0.0503**	−0.0511***	−0.0908***	−0.1131***
	(0.0283)	(0.0199)	(0.0189)	(0.0168)	(0.0401)
Tourism	−0.1262***	−0.0948**	−0.0970***	−0.1203***	−0.0906
	(0.0433)	(0.0376)	(0.0165)	(0.0148)	(0.0571)
Transport	−0.0554*	−0.0413**	−0.0399***	−0.0855***	−0.0883***
	(0.0318)	(0.0169)	(0.0145)	(0.0091)	(0.0176)
Finance	−0.0047	−0.0068	0.0146	0.0073	0.0435
	(0.0363)	(0.0187)	(0.0184)	(0.0189)	(0.0377)
Health	−0.1203*	−0.0766*	−0.0571**	−0.0546**	−0.0453
	(0.0622)	(0.0411)	(0.0225)	(0.0221)	(0.0344)
Telecommunication	−0.0144	−0.0024	0.0064	−0.0087	0.0168
	(0.0271)	(0.0158)	(0.0180)	(0.0186)	(0.0450)
Government Administration	−0.1179***	−0.0390*	−0.0102	−0.0462**	−0.0464
	(0.0438)	(0.0210)	(0.0128)	(0.0190)	(0.0344)
Education	−0.0020	−0.0214	−0.0092	−0.0481***	−0.0810**
	(0.0262)	(0.0205)	(0.0193)	(0.0159)	(0.0401)
AdminServices	−0.0803***	−0.0547*	−0.0292**	−0.0705***	−0.0813***
	(0.0271)	(0.0297)	(0.0135)	(0.0174)	(0.0290)
Permanent Contract	0.0123	0.0122	0.0068	−0.0143**	−0.0107
	(0.0179)	(0.0154)	(0.0092)	(0.0066)	(0.0119)
Large firm	0.1262***	0.0757***	0.0791***	0.0714***	0.0708***
	(0.0255)	(0.0137)	(0.0116)	(0.0078)	(0.0148)
Manager	−0.1020***	0.0251	0.0593***	0.1035***	0.1010***
	(0.0235)	(0.0232)	(0.0157)	(0.0158)	(0.0291)
Intermediate Profession	0.0462	0.0321***	0.0280**	0.0443***	0.0369*
	(0.0287)	(0.0123)	(0.0118)	(0.0110)	(0.0190)
Married	0.0392*	0.0366***	0.0465***	0.0547***	0.0460***
	(0.0203)	(0.0117)	(0.0080)	(0.0068)	(0.0122)
Kids	−0.0361*	−0.0108	0.0155*	0.0170***	0.0340***
	(0.0189)	(0.0112)	(0.0091)	(0.0060)	(0.0114)
Kids_10	0.0272	0.0246	0.0146	0.0276*	0.0131
	(0.0226)	(0.0154)	(0.0101)	(0.0150)	(0.0171)
University Performance	−0.0000	0.0004***	0.0006***	0.0008***	0.0006***
	(0.0005)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Knowledge of English	0.0165	0.0138	0.0254**	0.0239***	0.0192
	(0.0163)	(0.0114)	(0.0099)	(0.0064)	(0.0161)
Computer skill	0.1345***	0.1105***	0.0934***	0.0907***	0.0631***
	(0.0359)	(0.0209)	(0.0090)	(0.0098)	(0.0162)
University degree father	−0.0861	−0.0296	−0.0016	0.0293	0.0856**
	(0.0648)	(0.0238)	(0.0130)	(0.0332)	(0.0345)
University degree mother	0.0997***	0.0341**	0.0238	0.0101	−0.0250
	(0.0206)	(0.0154)	(0.0148)	(0.0247)	(0.0321)
Metropolitan area	−0.0542***	−0.0078	0.0086	0.0066	0.0115
	(0.0178)	(0.0123)	(0.0098)	(0.0091)	(0.0199)
North	0.2520***	0.1337***	0.0693***	0.0549***	0.0376***
	(0.0299)	(0.0148)	(0.0061)	(0.0101)	(0.0132)
Centre	0.2236***	0.1225***	0.0593***	0.0451***	0.0406***
	(0.0354)	(0.0201)	(0.0090)	(0.0055)	(0.0128)
Constant	0.5096***	1.0081***	1.2461***	1.4264***	1.5096***
	(0.0891)	(0.0612)	(0.0312)	(0.0433)	(0.0420)
Time effects	X	X	X	X	X
Number of observations	6754				
Pseudo R^2	0.1631	0.1316	0.1527	0.1871	0.2017

Bootstrap s.e. in parenthesis (800 replications). ***: significant at.99 level; **: significant at.95 level; *: significant at.90 level.

Table A8
Quantile regression of wage for males in public sector. Specification D.

	q10	q25	q50	q75	q90
Schooling	0.0118***	0.0126***	0.0122***	0.0180***	0.0251***
	(0.0039)	(0.0014)	(0.0021)	(0.0026)	(0.0031)
Experience	0.0356***	0.0274***	0.0259***	0.0270***	0.0267***
	(0.0046)	(0.0018)	(0.0011)	(0.0013)	(0.0021)
Experience^2	−0.0005***	−0.0003***	−0.0003***	−0.0003***	−0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agriculture	−0.0372	−0.0510	−0.1082	−0.0548	−0.0602
	(0.0583)	(0.0713)	(0.0704)	(0.1229)	(0.0604)
Manufacturing	0.0463	0.0482	0.0111	−0.0771**	−0.0833
	(0.0799)	(0.0413)	(0.0249)	(0.0386)	(0.1464)
Energy	0.0408	0.0349	−0.0284	−0.0347	−0.1340***
	(0.0747)	(0.0288)	(0.0273)	(0.0334)	(0.0339)
Construction	−0.0611	0.0730	0.0287	0.0131	−0.0203
	(0.0975)	(0.0523)	(0.0431)	(0.0876)	(0.0512)
Retail	−0.0726	−0.0506	−0.0895***	−0.1487***	−0.2026***
	(0.1131)	(0.0581)	(0.0339)	(0.0395)	(0.0319)
Tourism	−0.0387	0.0052	−0.0492	−0.0198	−0.1178
	(0.0882)	(0.0596)	(0.0431)	(0.0730)	(0.1389)
Transport	−0.0254	0.0551***	0.0113	0.0533*	−0.0003
	(0.0518)	(0.0164)	(0.0217)	(0.0312)	(0.0256)
Finance	−0.0683*	−0.0024	−0.0447**	−0.0148	−0.0295
	(0.0399)	(0.0252)	(0.0184)	(0.0397)	(0.1303)
Health	−0.0364	−0.0365**	−0.0747***	−0.1033***	−0.1391***
	(0.0351)	(0.0148)	(0.0216)	(0.0234)	(0.0301)
Telecommunication	−0.0515	−0.0212	0.0092	0.0350	−0.0139
	(0.0467)	(0.0295)	(0.0205)	(0.0230)	(0.0328)
Government Administration	−0.0213	−0.0108	−0.0400***	−0.0591***	−0.0719***
	(0.0166)	(0.0070)	(0.0140)	(0.0192)	(0.0272)
Education	−0.0236	−0.0112	−0.0357**	−0.0263	−0.0587***
	(0.0220)	(0.0143)	(0.0158)	(0.0170)	(0.0158)
AdminServices	−0.0190	0.0205	0.0369	0.0528*	−0.0160
	(0.0349)	(0.0161)	(0.0306)	(0.0272)	(0.0310)
Permanent Contract	0.0550*	0.0066	0.0400	0.0274	0.0156
	(0.0323)	(0.0203)	(0.0283)	(0.0249)	(0.0276)
Large firm	0.0092	−0.0033	0.0211	0.0094	−0.0014
	(0.0362)	(0.0247)	(0.0296)	(0.0323)	(0.0389)
Manager	0.0250***	0.0783***	0.1396***	0.2126***	0.2584***
	(0.0085)	(0.0118)	(0.0156)	(0.0251)	(0.0296)
Intermediate Profession	0.0110	0.0529***	0.0594***	0.0552***	0.0485***
	(0.0185)	(0.0134)	(0.0087)	(0.0109)	(0.0080)
Married	0.0387	0.0267*	0.0278**	0.0272*	0.0202
	(0.0267)	(0.0158)	(0.0135)	(0.0143)	(0.0254)
Kids	0.0333	0.0208	0.0140	0.0323**	0.0111
	(0.0254)	(0.0144)	(0.0157)	(0.0133)	(0.0224)
Kids_10	0.0504*	0.0514***	0.0789***	0.0539***	0.0340**
	(0.0264)	(0.0184)	(0.0141)	(0.0155)	(0.0153)
University Performance	0.0004	0.0006***	0.0014***	0.0023***	0.0023***
	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Knowledge of English	0.0256*	0.0187**	0.0233	0.0360***	0.0523***
	(0.0136)	(0.0083)	(0.0146)	(0.0137)	(0.0149)
Computer skill	0.0318*	0.0730***	0.0903***	0.0673***	0.0724***
	(0.0162)	(0.0083)	(0.0112)	(0.0119)	(0.0198)
University degree father	0.0595	0.0268*	0.0348***	−0.0308	−0.0397
	(0.0428)	(0.0156)	(0.0115)	(0.0193)	(0.0426)
University degree mother	−0.0339	−0.0407	−0.0485	0.0128	0.0369
	(0.0441)	(0.0388)	(0.0397)	(0.0367)	(0.0451)
Metropolitan area	−0.0116	−0.0084	−0.0196*	−0.0286***	−0.0062
	(0.0174)	(0.0076)	(0.0101)	(0.0092)	(0.0139)
North	−0.0093	−0.0063	−0.0043	0.0046	0.0294
	(0.0119)	(0.0106)	(0.0077)	(0.0080)	(0.0214)
Centre	0.0187***	−0.0051	0.0036	0.0387**	0.0842***
	(0.0068)	(0.0094)	(0.0117)	(0.0159)	(0.0218)
Constant	1.1322***	1.3228***	1.4399***	1.4944***	1.5631***
	(0.0898)	(0.0504)	(0.0558)	(0.0533)	(0.0425)
Time effects	X	X	X	X	X
Number of observations	5243				
Pseudo R^2	0.1461	0.1407	0.1612	0.2312	0.2911

Bootstrap s.e. in parenthesis (800 replications). ***: significant at.99 level; **: significant at.95 level; *: significant at.90 level.

Table A9
Quantile regression of wage for females in public sector. Specification D.

	q10	q25	q50	q75	q90
Schooling	0.0193∗∗∗	0.0158∗∗∗	0.0168∗∗∗	0.0149∗∗∗	0.0177∗∗∗
	(0.0038)	(0.0027)	(0.0032)	(0.0020)	(0.0047)
Experience	0.0296∗∗∗	0.0214∗∗∗	0.0138∗∗∗	0.0148∗∗∗	0.0211∗∗∗
	(0.0025)	(0.0020)	(0.0015)	(0.0017)	(0.0022)
Experience^2	−0.0004∗∗∗	−0.0003∗∗∗	−0.0001∗∗∗	−0.0001∗∗∗	−0.0002∗∗∗
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agriculture	−0.1228	−0.0815∗∗	−0.1043∗∗	−0.1671	0.0635
	(0.1233)	(0.0383)	(0.0413)	(0.1645)	(0.1801)
Manufacturing	−0.1091	−0.1793∗	−0.1187∗	−0.0521	−0.1520
	(0.2684)	(0.1008)	(0.0635)	(0.0804)	(0.1126)
Energy	−0.0484	0.0065	−0.0296	−0.0408	0.0858
	(0.1197)	(0.0981)	(0.0304)	(0.0460)	(0.1386)
Construction	0.0748	−0.0211	−0.1162∗∗	−0.1325∗	−0.1923∗∗∗
	(0.0981)	(0.0322)	(0.0531)	(0.0784)	(0.0472)
Retail	−0.3275∗∗	−0.1433	−0.1111∗∗∗	−0.1005∗	−0.0600
	(0.1414)	(0.0892)	(0.0355)	(0.0595)	(0.0692)
Tourism	0.0454	−0.0224	−0.0572	−0.0525	−0.0037
	(0.1061)	(0.0544)	(0.0834)	(0.0470)	(0.0756)
Transport	−0.0261	−0.0565∗∗	−0.0277	0.0221	0.0340
	(0.0975)	(0.0249)	(0.0636)	(0.0430)	(0.0669)
Finance	−0.0176	−0.0241	−0.0290∗	−0.0610∗∗∗	−0.0234
	(0.0235)	(0.0182)	(0.0154)	(0.0185)	(0.0386)
Health	−0.0551∗	−0.0371∗∗	−0.0246	−0.0411∗∗∗	−0.0349
	(0.0319)	(0.0184)	(0.0191)	(0.0153)	(0.0215)
Telecommunication	−0.0015	−0.0184	0.0236	0.0254	−0.0201
	(0.0400)	(0.0414)	(0.0253)	(0.0207)	(0.0206)
Government Administration	−0.0188	−0.0118	−0.0060	−0.0290	−0.0461
	(0.0222)	(0.0140)	(0.0127)	(0.0180)	(0.0314)
Education	−0.0153	−0.0193∗	0.0060	−0.0095	0.0109
	(0.0285)	(0.0110)	(0.0173)	(0.0126)	(0.0233)
AdminServices	0.0127	0.0206	0.0403∗∗∗	0.0204	0.0369
	(0.0253)	(0.0128)	(0.0149)	(0.0189)	(0.0230)
Permanent Contract	−0.0026	−0.0095	−0.0019	−0.0107	−0.0042
	(0.0356)	(0.0189)	(0.0167)	(0.0078)	(0.0221)
Large firm	0.0395	0.0119	0.0244	0.0405∗∗∗	0.0862∗∗∗
	(0.0440)	(0.0278)	(0.0204)	(0.0129)	(0.0210)
Manager	0.0124	0.0521∗∗∗	0.0835∗∗∗	0.1552∗∗∗	0.2542∗∗∗
	(0.0210)	(0.0157)	(0.0161)	(0.0151)	(0.0386)
Intermediate Profession	0.0238∗∗	0.0442∗∗∗	0.0530∗∗∗	0.0535∗∗∗	0.0420∗∗
	(0.0119)	(0.0076)	(0.0117)	(0.0123)	(0.0184)
Married	0.0231∗∗	0.0256∗∗	0.0181∗∗	0.0297∗∗∗	0.0212
	(0.0113)	(0.0124)	(0.0092)	(0.0097)	(0.0143)
Kids	−0.0014	0.0014	0.0071	0.0013	0.0196
	(0.0128)	(0.0078)	(0.0115)	(0.0084)	(0.0168)
Kids_10	0.0334	0.0202	0.0080	0.0062	−0.0054
	(0.0237)	(0.0172)	(0.0104)	(0.0098)	(0.0176)
University Performance	0.0004∗∗∗	0.0007∗∗∗	0.0008∗∗∗	0.0011∗∗∗	0.0015∗∗∗
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Knowledge of English	−0.0287	−0.0123	−0.0079	0.0038	−0.0091
	(0.0268)	(0.0087)	(0.0084)	(0.0123)	(0.0109)
Computer skill	0.0345∗∗∗	0.0305∗	0.0210	0.0382∗∗∗	0.0273
	(0.0131)	(0.0174)	(0.0129)	(0.0098)	(0.0271)
University degree father	−0.0273	−0.0030	0.0244	0.0925∗∗∗	0.1164∗∗
	(0.0177)	(0.0217)	(0.0154)	(0.0188)	(0.0451)
University degree mother	−0.0237	−0.0189	−0.0065	−0.0162	0.0064
	(0.0564)	(0.0264)	(0.0154)	(0.0300)	(0.0355)
Metropolitan area	−0.0098	−0.0056	−0.0109∗∗	−0.0195∗∗	−0.0134
	(0.0187)	(0.0089)	(0.0050)	(0.0076)	(0.0116)
North	0.0167	−0.0056	−0.0016	−0.0001	−0.0079
	(0.0264)	(0.0101)	(0.0099)	(0.0068)	(0.0158)
Centre	0.0030	−0.0083	−0.0062	0.0055	0.0228
	(0.0187)	(0.0115)	(0.0072)	(0.0094)	(0.0154)
Constant	1.1157∗∗∗	1.3961∗∗∗	1.5493∗∗∗	1.6540∗∗∗	1.6431∗∗∗
	(0.0999)	(0.0481)	(0.0474)	(0.0352)	(0.0614)
Time effects	X	X	X	X	X
Number of observations	4714				
Pseudo R^2	0.134	0.1219	0.1417	0.1722	0.2483

Bootstrap s.e. in parenthesis (800 replications). ∗∗∗: significant at.99 level; ∗∗: significant at.95 level; ∗: significant at.90 level.

Table A10
Fixed effects quantile regression of wage for males in private sector. Specification D.

	q10	q25	q50	q75	q90
Schooling	0.0049**	0.0061**	0.0056***	0.0053***	0.0029
	(0.0024)	(0.0024)	(0.0011)	(0.0020)	(0.0038)
Experience	0.0311***	0.0247***	0.0224***	0.0204***	0.0172***
	(0.0023)	(0.0009)	(0.0008)	(0.0016)	(0.0032)
Experience^2	−0.0004***	−0.0003***	−0.0002***	−0.0001***	−0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agriculture	−0.0765	−0.0854	−0.0644***	−0.0846***	−0.1066
	(0.0577)	(0.0607)	(0.0215)	(0.0319)	(0.0727)
Manufacturing	−0.0174	−0.0282	−0.0008	−0.0032	0.0381
	(0.0393)	(0.0204)	(0.0083)	(0.0133)	(0.0332)
Energy	0.0807***	0.0367***	0.0474***	0.0551***	0.0752**
	(0.0234)	(0.0088)	(0.0119)	(0.0183)	(0.0349)
Construction	0.0034	−0.0331*	0.0042	−0.0049	0.0450
	(0.0462)	(0.0196)	(0.0060)	(0.0194)	(0.0531)
Retail	−0.0141	−0.0135	0.0103	0.0130	0.0262
	(0.0355)	(0.0151)	(0.0107)	(0.0124)	(0.0194)
Tourism	−0.0338	−0.0074	0.0003	0.0085	0.0395
	(0.0386)	(0.0216)	(0.0124)	(0.0212)	(0.0316)
Transport	−0.0317	−0.0105	0.0097	0.0016	0.0137
	(0.0363)	(0.0139)	(0.0090)	(0.0123)	(0.0311)
Finance	−0.0040	−0.0036	0.0201	0.0218*	0.0246
	(0.0393)	(0.0142)	(0.0133)	(0.0118)	(0.0272)
Health	0.0082	0.0010	0.0109	0.0118	0.0095
	(0.0448)	(0.0195)	(0.0173)	(0.0220)	(0.0566)
Telecommunication	0.0060	0.0160	0.0359***	0.0220**	0.0407*
	(0.0388)	(0.0163)	(0.0083)	(0.0108)	(0.0225)
Government Administration	−0.0047	−0.0032	0.0050	−0.0153	−0.0003
	(0.0443)	(0.0160)	(0.0104)	(0.0242)	(0.0243)
Education	0.0532	0.0661***	0.0694***	0.0631**	0.0778*
	(0.0404)	(0.0168)	(0.0166)	(0.0273)	(0.0420)
AdminServices	−0.0205	−0.0110	0.0050	−0.0174	0.0341
	(0.0348)	(0.0238)	(0.0118)	(0.0185)	(0.0595)
Permanent Contract	−0.0416	−0.0027	0.0086	−0.0011	−0.0313
	(0.0296)	(0.0127)	(0.0071)	(0.0140)	(0.0261)
Large firm	0.0239**	0.0242***	0.0278***	0.0336***	0.0291
	(0.0100)	(0.0059)	(0.0052)	(0.0094)	(0.0244)
Manager	−0.0698**	−0.0053	0.0066	0.0241**	0.0709**
	(0.0306)	(0.0119)	(0.0078)	(0.0105)	(0.0283)
Intermediate Profession	0.0125	0.0292***	0.0329***	0.0428***	0.0558***
	(0.0130)	(0.0088)	(0.0053)	(0.0074)	(0.0092)
Married	0.0298*	0.0458***	0.0526***	0.0591***	0.0740***
	(0.0159)	(0.0111)	(0.0068)	(0.0119)	(0.0112)
Kids	−0.0307	−0.0251***	−0.0236***	−0.0315***	−0.0351***
	(0.0211)	(0.0093)	(0.0049)	(0.0099)	(0.0106)
Kids_10	−0.0534***	−0.0582***	−0.0491***	−0.0595***	−0.0981***
	(0.0192)	(0.0072)	(0.0069)	(0.0119)	(0.0229)
University Performance	0.0009***	0.0007***	0.0009***	0.0011***	0.0014***
	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Knowledge of English	0.0521***	0.0483***	0.0472***	0.0472***	0.0488***
	(0.0136)	(0.0051)	(0.0046)	(0.0078)	(0.0148)
Computer skill	−0.0195	0.0082	−0.0068	−0.0161*	−0.0311
	(0.0216)	(0.0098)	(0.0086)	(0.0092)	(0.0416)
University degree father	−0.0004	−0.0488***	−0.0525***	−0.0565***	−0.0649***
	(0.0433)	(0.0156)	(0.0103)	(0.0094)	(0.0183)
University degree mother	0.2217***	0.3180***	0.3109***	0.3059***	0.3781***
	(0.0507)	(0.0170)	(0.0130)	(0.0321)	(0.0664)
Metropolitan area	−0.0154*	0.0025	−0.0083**	−0.0166**	−0.0002
	(0.0086)	(0.0077)	(0.0035)	(0.0075)	(0.0159)
North	0.3527***	0.3497***	0.3461***	0.3432***	0.3493***
	(0.0144)	(0.0103)	(0.0068)	(0.0064)	(0.0236)
Centre	0.2772***	0.2890***	0.2808***	0.2796***	0.2775***
	(0.0268)	(0.0120)	(0.0049)	(0.0069)	(0.0286)
Constant	1.2965***	1.3236***	1.4078***	1.5219***	1.6944***
	(0.0382)	(0.0335)	(0.0199)	(0.0385)	(0.0793)
Time effects	X	X	X	X	X
Number of observations	7685				
Pseudo R^2	0.3615	0.4244	0.4674	0.4206	0.3296

Bootstrap s.e. in parenthesis (800 replications). ***: significant at.99 level; **: significant at.95 level; *: significant at.90 level.

Table A11
Fixed effects quantile regression of wage for females in private sector. Specification D.

	q10	q25	q50	q75	q90
Schooling	0.0022	0.0063**	0.0052***	0.0062***	0.0082***
	(0.0023)	(0.0027)	(0.0017)	(0.0022)	(0.0021)
Experience	0.0144***	0.0187***	0.0170***	0.0159***	0.0162***
	(0.0025)	(0.0008)	(0.0006)	(0.0011)	(0.0034)
Experience^2	−0.0002***	−0.0003***	−0.0003***	−0.0003***	−0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agriculture	0.0890**	0.0143	0.0219	0.0079	−0.0811***
	(0.0435)	(0.0212)	(0.0370)	(0.0224)	(0.0267)
Manufacturing	−0.0406	−0.0445***	−0.0374***	−0.0465***	−0.0729***
	(0.0306)	(0.0168)	(0.0123)	(0.0152)	(0.0168)
Energy	−0.0414	−0.0510***	−0.0541***	−0.0536***	−0.0316
	(0.0409)	(0.0140)	(0.0151)	(0.0137)	(0.0286)
Construction	−0.0289	−0.0223	−0.0012	−0.0013	−0.0209
	(0.0468)	(0.0293)	(0.0325)	(0.0397)	(0.0300)
Retail	−0.0564*	−0.0515***	−0.0466***	−0.0472***	−0.0658***
	(0.0308)	(0.0156)	(0.0106)	(0.0169)	(0.0195)
Tourism	−0.0680**	−0.0318*	−0.0260**	−0.0124	−0.0065
	(0.0296)	(0.0188)	(0.0117)	(0.0219)	(0.0416)
Transport	−0.0356	−0.0477***	−0.0505***	−0.0666***	−0.0831***
	(0.0383)	(0.0082)	(0.0072)	(0.0101)	(0.0261)
Finance	0.0201	0.0112	0.0116	0.0138	0.0347
	(0.0226)	(0.0142)	(0.0087)	(0.0204)	(0.0266)
Health	0.0226	0.0218	0.0238*	0.0219**	0.0188
	(0.0402)	(0.0187)	(0.0129)	(0.0103)	(0.0257)
Telecommunication	0.0322	0.0246	0.0138	−0.0062	−0.0060
	(0.0417)	(0.0188)	(0.0113)	(0.0186)	(0.0131)
Government Administration	−0.0047	−0.0218	−0.0243**	−0.0254	−0.0113
	(0.0380)	(0.0189)	(0.0116)	(0.0220)	(0.0271)
Education	0.0276	0.0346*	0.0161	0.0105	−0.0176
	(0.0275)	(0.0185)	(0.0112)	(0.0121)	(0.0195)
AdminServices	0.0196	0.0138	0.0080	−0.0024	−0.0136
	(0.0307)	(0.0167)	(0.0067)	(0.0156)	(0.0202)
Permanent Contract	−0.0190*	−0.0117	−0.0101	−0.0178**	−0.0285*
	(0.0101)	(0.0072)	(0.0078)	(0.0080)	(0.0152)
Large firm	0.0335***	0.0262***	0.0236***	0.0215***	0.0115
	(0.0111)	(0.0071)	(0.0050)	(0.0060)	(0.0091)
Manager	0.0317	0.0254***	0.0460***	0.0662***	0.0584**
	(0.0294)	(0.0082)	(0.0138)	(0.0150)	(0.0264)
Intermediate Profession	0.0385*	0.0341***	0.0335***	0.0325***	0.0477**
	(0.0212)	(0.0094)	(0.0069)	(0.0097)	(0.0186)
Married	0.0421***	0.0308***	0.0337***	0.0334***	0.0300***
	(0.0158)	(0.0063)	(0.0040)	(0.0080)	(0.0111)
Kids	−0.0173	−0.0192***	−0.0036	0.0145**	0.0075
	(0.0154)	(0.0044)	(0.0042)	(0.0070)	(0.0082)
Kids_10	0.0589***	0.0678***	0.0498***	0.0418***	0.0669***
	(0.0198)	(0.0055)	(0.0056)	(0.0109)	(0.0207)
University Performance	0.0002	0.0001	0.0001**	0.0000	−0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Knowledge of English	0.0120	0.0148**	0.0185***	0.0250***	0.0337***
	(0.0138)	(0.0061)	(0.0040)	(0.0068)	(0.0102)
Computer skill	0.0513***	0.0314**	0.0311***	0.0198*	0.0349*
	(0.0189)	(0.0126)	(0.0076)	(0.0109)	(0.0182)
University degree father	0.0278	0.0754***	0.0789***	0.0991**	0.1361***
	(0.0477)	(0.0104)	(0.0104)	(0.0412)	(0.0313)
University degree mother	0.0247	0.0121	−0.0021	−0.0310*	−0.0056
	(0.0387)	(0.0107)	(0.0097)	(0.0167)	(0.0360)
Metropolitan area	−0.0009	0.0058	0.0146***	0.0148**	0.0178
	(0.0095)	(0.0065)	(0.0029)	(0.0065)	(0.0138)
North	−0.0235	−0.0591***	−0.0625***	−0.0687***	−0.0956***
	(0.0146)	(0.0083)	(0.0086)	(0.0103)	(0.0205)
Centre	0.1835***	0.1600***	0.1562***	0.1545***	0.1419***
	(0.0195)	(0.0120)	(0.0095)	(0.0099)	(0.0208)
Constant	1.6102***	1.6234***	1.7123***	1.7640***	1.8584***
	(0.0647)	(0.0309)	(0.0181)	(0.0283)	(0.0315)
Time effects	X	X	X	X	X
Number of observations	6754				
Pseudo R^2	0.2402	0.308	0.3447	0.333	0.2945

Bootstrap s.e. in parenthesis (800 replications). ***: significant at.99 level; **: significant at.95 level; *: significant at.90 level.

Table A12
Fixed effects quantile regression of wage for males in public sector. Specification D.

	q10	q25	q50	q75	q90
Schooling	0.0123***	0.0046***	0.0025***	0.0018	0.0010
	(0.0027)	(0.0013)	(0.0009)	(0.0021)	(0.0044)
Experience	0.0303***	0.0289***	0.0273***	0.0271***	0.0292***
	(0.0028)	(0.0018)	(0.0006)	(0.0012)	(0.0030)
Experience^2	−0.0005***	−0.0005***	−0.0004***	−0.0004***	−0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agriculture	0.0964**	0.0764*	0.0244*	−0.0185	−0.0555
	(0.0488)	(0.0458)	(0.0142)	(0.0118)	(0.0521)
Manufacturing	0.2143***	0.2038***	0.1812***	0.1117	0.2435**
	(0.0440)	(0.0356)	(0.0129)	(0.0828)	(0.1151)
Energy	0.0323	0.0222	−0.0014	−0.0253	−0.0066
	(0.0299)	(0.0200)	(0.0139)	(0.0170)	(0.0445)
Construction	0.0092	−0.0540	−0.0334	0.0206	−0.0261
	(0.0685)	(0.0775)	(0.0966)	(0.1491)	(0.1559)
Retail	0.1099	0.0071	0.0513	0.0161	−0.0318
	(0.1387)	(0.0411)	(0.0477)	(0.0190)	(0.0431)
Tourism	−0.3593**	−0.1433***	−0.1561***	−0.2078***	−0.2285***
	(0.1739)	(0.0360)	(0.0123)	(0.0129)	(0.0453)
Transport	0.0167	0.0107	0.0057	−0.0042	0.0257
	(0.0172)	(0.0108)	(0.0117)	(0.0175)	(0.0230)
Finance	−0.0437	−0.0502**	−0.0645**	−0.0630***	−0.0701***
	(0.0958)	(0.0216)	(0.0260)	(0.0212)	(0.0256)
Health	−0.0161	−0.0268	−0.0179**	−0.0355***	−0.0427
	(0.0323)	(0.0184)	(0.0072)	(0.0123)	(0.0314)
Telecommunication	0.0319	−0.0189	0.0134	−0.0018	−0.0011
	(0.0319)	(0.0252)	(0.0142)	(0.0158)	(0.0381)
Government Administration	0.0184	0.0004	−0.0033	−0.0101	0.0051
	(0.0291)	(0.0066)	(0.0065)	(0.0097)	(0.0223)
Education	−0.0106	−0.0162*	−0.0157**	−0.0210*	−0.0192
	(0.0338)	(0.0085)	(0.0068)	(0.0119)	(0.0139)
AdminServices	0.0815***	0.0523***	0.0549***	0.0648***	0.0695*
	(0.0290)	(0.0143)	(0.0149)	(0.0242)	(0.0381)
Permanent Contract	−0.0140	−0.0443***	−0.0255**	−0.0570***	−0.0473*
	(0.0408)	(0.0118)	(0.0109)	(0.0166)	(0.0246)
Large firm	−0.0705*	−0.0841***	−0.0741***	−0.0909***	−0.0922***
	(0.0401)	(0.0199)	(0.0183)	(0.0188)	(0.0250)
Manager	−0.0298**	0.0035	0.0058	0.0434***	0.0400**
	(0.0146)	(0.0071)	(0.0056)	(0.0095)	(0.0183)
Intermediate Profession	−0.0187	−0.0174**	−0.0128***	−0.0062	−0.0086
	(0.0174)	(0.0084)	(0.0046)	(0.0065)	(0.0111)
Married	−0.0305	−0.0205**	−0.0189***	−0.0107	−0.0309
	(0.0256)	(0.0088)	(0.0055)	(0.0118)	(0.0203)
Kids	0.0674***	0.0669***	0.0759***	0.0841***	0.1047***
	(0.0253)	(0.0058)	(0.0062)	(0.0066)	(0.0172)
Kids_10	−0.0297	−0.0050	0.0008	0.0076	0.0188
	(0.0314)	(0.0090)	(0.0062)	(0.0108)	(0.0286)
University Performance	0.0015***	0.0014***	0.0015***	0.0016***	0.0022***
	(0.0003)	(0.0001)	(0.0000)	(0.0001)	(0.0003)
Knowledge of English	0.0069	−0.0065	0.0091*	−0.0080	−0.0036
	(0.0142)	(0.0086)	(0.0048)	(0.0112)	(0.0123)
Computer skill	0.0653***	0.0698***	0.0673***	0.0740***	0.0868***
	(0.0133)	(0.0080)	(0.0072)	(0.0113)	(0.0238)
University degree father	−0.1305***	−0.1053***	−0.0860***	−0.0456*	−0.0515
	(0.0257)	(0.0189)	(0.0219)	(0.0236)	(0.0317)
University degree mother	0.2658***	0.2866***	0.2975***	0.3053***	0.3011***
	(0.0899)	(0.0295)	(0.0346)	(0.0383)	(0.0359)
Metropolitan area	0.0750***	0.0686***	0.0675***	0.0616***	0.0452***
	(0.0130)	(0.0031)	(0.0052)	(0.0084)	(0.0142)
North	−0.0581***	−0.0457***	−0.0522***	−0.0514***	−0.0505***
	(0.0168)	(0.0090)	(0.0061)	(0.0053)	(0.0121)
Centre	0.1924***	0.2065***	0.2055***	0.2038***	0.2003***
	(0.0134)	(0.0069)	(0.0075)	(0.0067)	(0.0203)
Constant	1.7985***	1.8076***	1.8383***	1.8979***	1.8989***
	(0.0749)	(0.0358)	(0.0215)	(0.0299)	(0.0476)
Time effects	X	X	X	X	X
Number of observations	5243				
Pseudo R^2	0.2475	0.3184	0.3702	0.3812	0.3469

Bootstrap s.e. in parenthesis (800 replications). ***: significant at.99 level; **: significant at.95 level; *: significant at.90 level.

Table A13
Fixed effects quantile regression of wage for females in public sector. Specification D.

	q10	q25	q50	q75	q90
Schooling	0.0073∗	0.0070∗∗∗	0.0049∗∗∗	0.0041∗∗∗	−0.0028
	(0.0039)	(0.0025)	(0.0015)	(0.0013)	(0.0025)
Experience	0.0057∗∗∗	0.0070∗∗∗	0.0069∗∗∗	0.0070∗∗∗	0.0103∗∗∗
	(0.0019)	(0.0010)	(0.0010)	(0.0012)	(0.0024)
Experience^2	−0.0000	−0.0000∗∗	−0.0000∗∗	−0.0000	−0.0001∗
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agriculture	−0.0040	−0.0881∗∗∗	−0.1111∗∗∗	−0.1190∗∗∗	−0.1366∗∗∗
	(0.0487)	(0.0234)	(0.0283)	(0.0374)	(0.0322)
Manufacturing	−0.1456∗∗	−0.0786	−0.0891	−0.0621	0.0713
	(0.0574)	(0.0693)	(0.0791)	(0.1013)	(0.1294)
Energy	−0.0031	−0.0517∗∗∗	−0.0942∗∗∗	−0.0350	0.0302
	(0.0156)	(0.0102)	(0.0342)	(0.0929)	(0.0832)
Construction	0.0900∗∗∗	−0.0130	−0.0038	0.0399	−0.0168
	(0.0275)	(0.0210)	(0.0589)	(0.0779)	(0.0646)
Retail	−0.1094	−0.1314∗∗∗	−0.1289∗∗∗	−0.1361∗∗∗	−0.0977∗∗
	(0.0668)	(0.0351)	(0.0219)	(0.0327)	(0.0443)
Tourism	−0.0166	0.0727	0.0631∗∗	0.0521	0.3260∗∗
	(0.0780)	(0.0494)	(0.0320)	(0.1589)	(0.1425)
Transport	0.0111	−0.0292	−0.0242	−0.0097	−0.0468
	(0.0386)	(0.0342)	(0.0231)	(0.0285)	(0.0873)
Finance	−0.1530∗∗∗	−0.1102∗∗	−0.0667∗∗∗	−0.0707∗∗	−0.0737∗
	(0.0567)	(0.0460)	(0.0115)	(0.0341)	(0.0379)
Health	−0.0486∗∗∗	−0.0370∗∗∗	−0.0181∗∗∗	−0.0281∗∗	−0.0276
	(0.0154)	(0.0082)	(0.0056)	(0.0142)	(0.0232)
Telecommunication	−0.0127	0.0435∗∗	0.0881∗∗∗	0.0776	0.3267∗
	(0.0407)	(0.0201)	(0.0184)	(0.0533)	(0.1926)
Government Administration	−0.0165	−0.0114	0.0019	−0.0065	0.0002
	(0.0109)	(0.0107)	(0.0072)	(0.0113)	(0.0208)
Education	−0.0225	−0.0180∗∗	−0.0082	−0.0028	0.0147
	(0.0173)	(0.0072)	(0.0084)	(0.0167)	(0.0174)
AdminServices	−0.0340	−0.0425∗∗∗	−0.0282∗∗∗	−0.0292∗	−0.0186
	(0.0243)	(0.0157)	(0.0069)	(0.0152)	(0.0398)
Permanent Contract	−0.0627∗∗∗	−0.0276∗∗	−0.0175∗∗	−0.0152	−0.0263
	(0.0217)	(0.0125)	(0.0083)	(0.0136)	(0.0203)
Large firm	−0.0638∗∗∗	−0.0259∗	−0.0250∗∗∗	−0.0257∗∗	−0.0506∗∗∗
	(0.0220)	(0.0132)	(0.0080)	(0.0111)	(0.0190)
Manager	−0.0129	0.0086∗	0.0172∗∗∗	0.0261∗∗	0.0389∗∗
	(0.0178)	(0.0050)	(0.0061)	(0.0105)	(0.0163)
Intermediate Profession	−0.0415∗∗	−0.0176∗∗∗	−0.0229∗∗	−0.0144	−0.0273∗∗
	(0.0200)	(0.0065)	(0.0089)	(0.0097)	(0.0132)
Married	−0.0205∗	−0.0214∗∗∗	−0.0227∗∗∗	−0.0226∗∗∗	−0.0267∗∗∗
	(0.0117)	(0.0078)	(0.0050)	(0.0030)	(0.0093)
Kids	0.0065	0.0034	0.0058	0.0140∗∗∗	0.0120
	(0.0088)	(0.0038)	(0.0046)	(0.0039)	(0.0113)
Kids_10	−0.0151	−0.0205∗	−0.0229∗∗∗	−0.0331∗∗∗	−0.0296
	(0.0180)	(0.0119)	(0.0041)	(0.0064)	(0.0181)
University Performance	0.0011∗∗∗	0.0012∗∗∗	0.0012∗∗∗	0.0012∗∗∗	0.0013∗∗∗
	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Knowledge of English	0.0126	0.0272∗∗∗	0.0414∗∗∗	0.0572∗∗∗	0.0840∗∗∗
	(0.0107)	(0.0061)	(0.0035)	(0.0051)	(0.0187)
Computer skill	0.0657∗∗∗	0.0644∗∗∗	0.0682∗∗∗	0.0780∗∗∗	0.1034∗∗∗
	(0.0118)	(0.0092)	(0.0050)	(0.0077)	(0.0162)
University degree father	−0.0104	−0.0028	−0.0124∗	−0.0182∗∗	−0.0230
	(0.0391)	(0.0097)	(0.0071)	(0.0073)	(0.0455)
University degree mother	0.2257∗∗∗	0.2369∗∗∗	0.2227∗∗∗	0.2218∗∗∗	0.2995∗∗∗
	(0.0623)	(0.0132)	(0.0157)	(0.0289)	(0.1051)
Metropolitan area	−0.0673∗∗∗	−0.0571∗∗∗	−0.0593∗∗∗	−0.0567∗∗∗	−0.0617∗∗∗
	(0.0101)	(0.0062)	(0.0037)	(0.0083)	(0.0144)
North	0.0292∗∗∗	0.0174∗∗∗	0.0252∗∗∗	0.0225∗∗∗	0.0206∗
	(0.0110)	(0.0065)	(0.0043)	(0.0043)	(0.0110)
Centre	0.0302∗∗	0.0297∗∗∗	0.0376∗∗∗	0.0368∗∗∗	0.0468∗∗∗
	(0.0146)	(0.0080)	(0.0037)	(0.0050)	(0.0095)
Constant	2.1414∗∗∗	2.1429∗∗∗	2.1391∗∗∗	2.1708∗∗∗	2.2348∗∗∗
	(0.0581)	(0.0344)	(0.0236)	(0.0333)	(0.0426)
Time effects	X	X	X	X	X
Number of observations	4714				
Pseudo R^2	0.1319	0.2014	0.2652	0.2778	0.2522

Bootstrap s.e. in parenthesis (800 replications). ∗∗∗: significant at.99 level; ∗∗: significant at.95 level; ∗: significant at.90 level.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2018.09.025.

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