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DETAILED RIF DECOMPOSITION WITH SELECTION - THE GENDER PAY GAP IN ITALY-

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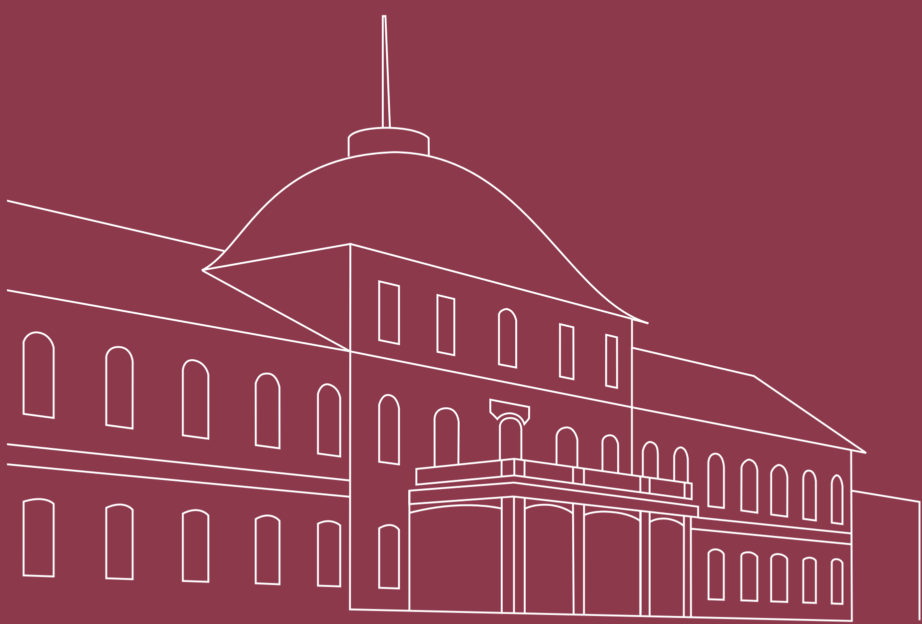

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Detailed RIF Decomposition with Selection – The Gender Pay Gap in Italy –*

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Abstract

In this paper, we estimate the gender pay gap along the wage distribution using a detailed decomposition approach based on unconditional quantile regressions. Non-randomness of the sample leads to biased and inconsistent estimates of the wage equation as well as of the components of the wage gap. Therefore, the method is extended to account for sample selection problems. The decomposition is conducted by using Italian microdata. Accounting for labor market selection may be particularly relevant for Italy given a comparably low female labor market participation rate. The results suggest not only differences in the income gap along the wage distribution (in particular glass ceiling), but also differences in the contribution of selection effects to the pay gap at different quantiles.

Keywords: Gender Pay Gap, Detailed Decomposition, Unconditional Quantile Regression, Sample Selection.

JEL - Classification: J7, J13, J310

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1 Introduction

Gender differences in pay are a well-known phenomenon of modern labor markets. Despite the promotion of equal-pay legislation and equal-pay opportunities, differences in pay between men and women persist (Blau and Kahn, 1992, 2003, 2006; Goldin, 2014; Kahn, 2015; Blau and Kahn, 2016). Adding to the broad literature on the Gender Pay Gap (GPG) research has recently focused on the estimation of the wage gap beyond the mean (Albrecht et al., 2003; Machado and Mata, 2005; Melly, 2005a, 2005b; Lucifora and Meurs, 2006; Arulampalam et al., 2007; Albrecht et al., 2009; Longhi et al., 2012; Xiu and Gunderson, 2014). Analyzing the GPG along the wage distribution allows to gain additional insights compared to the mean estimation. In particular, the phenomena of glass ceiling and sticky floors, i.e. more pronounced pay gaps at the top and bottom of the wage distribution, have been revealed using quantile-regression approaches. Hence, estimation beyond the mean allows to study gender wage inequality across the wage distribution. The standard approach in modern labor economics when it comes to decomposition methods is the Oaxaca (1973) and Blinder (1973) method. Advantages of the Oaxaca-Blinder decomposition are its relatively simple implementation and intuitive approach.[1] In the literature, the unexplained component, i.e. the part due to differences in coefficients, is thereby identified as a major contributor to the wage gap (e.g. Blau and Kahn, 2016). A detailed decomposition allows to gain information on the contribution of various personal, labor market or job characteristics to the GPG. However, it implies additional functional form restrictions to identify the various elements of the detailed decomposition. This holds in particular, when the decomposition is conducted beyond the mean (Fortin et al., 2011; Longhi et al., 2012). A popular approach is the method proposed by Machado and Mata (2005) based on Conditional Quantile Regression (CQR). The detailed decomposition, however, is path dependent, i.e. the order of the decomposition matters (Fortin et al., 2011). Moreover, the method is computationally intense as it calculates the entire conditional wage distribution and uses simulation techniques to calculate the counterfactuals. Most importantly, the method based on standard CQRs does not allow for the unconditional mean interpretation. The latter, however, is used in Oaxaca-Blinder type decompositions. Despite the estimation beyond the mean, it is important to control for group-specific sample selection. Indeed, gender differences occur when it comes to labor market participation (Heckman, 1979). Biases due to differences between men and women in the propensity to work may be important in determining the GPG and failure to account for this bias may result in inaccurate and biased estimation of the gender-specific wage equations. Consequently, also the components of the pay differential may be biased. The underlying study is applied on Italian microdata. The Italian case is particularly interesting for the study of sample selection as gender differences in labor market participation are particularly pronounced in Italy. The female labor force participation in Italy amounted to 50.6% in 2015, while the

[1] The method is easy to implement as it is estimated via OLS and by decomposing the pay gap in an explained and unexplained part, it provides an intuitive interpretation of the results.

EU-28 average was at more than 64.0% in the same year (Eurostat, 2016). Albrecht et al. (2009) extend the method by Machado and Mata (2005) to account for sample selection showing that sample selection along the wage distribution is important when considering pay differences between full- and part-time female employees in the Netherlands.

This paper uses linear Recentered Influence Function (RIF)-OLS regressions to estimate Mincer-type wage equations for men and women (Firpo et al., 2009b). Estimation at specific quantiles is thereby based on Unconditional Quantile Regression (UQR).[2] The method has the advantage that it allows to compute a detailed decomposition in a path-independent way and that it allows for the unconditional mean interpretation of the coefficient estimates.[3] In case of concerns of nonlineartiy, the method may be combined with a reweighting scheme. For robustness, we apply the reweighting scheme proposed by DiNardo et al. (1996) and show that the results do not change significantly. The main part of the paper focuses on the extension of the quantile-specific RIF-OLS decomposition to account for selection into employment. Thereby, consistent estimates of the components of the GPG along the wage distribution are obtained. The method by Firpo et al. (2009b) is one of the very few approaches allowing to conduct detailed Oaxaca-Blinder type decompositions beyond the mean. Thereby, the model allows to calculate the significance of gender differences in endowments as well as in coefficients at different points of the wage distribution. In the extended model, the selection effect can be attributed to the endowments and coefficients part, respectively, explicitly showing the contribution of (otherwise) unobservable characteristics to the different parts of the GPG. The selection correction terms are estimated using both parametric and semiparametric single-index models. The semiparametric binary choice models applied are the Ichimura (1993) and Klein and Spady (1993) models. The parametric model estimates the incidence of employment via probit estimation. Sample-selection bias correction is generally conducted via parametric regression models such as maximum likelihood probit or logit, which assume normally distributed errors. However, distributional assumptions may play an important role in sample selection models (Martins, 2001). Semiparametric binary choice estimators, such as the Ichimura and Klein-Spady estimator, do not require any distributional assumptions. The semiparametric selection correction terms obtained are then, via polynomial regression, included in the respective wage equations correcting for selection bias at the specific quantiles. As the semiparametric models applied are computationally costly, a two-point wild-bootstrap test based on Horowitz and Härdle (1994) compares the estimation outcome from the parametric and semiparametric binary choice models. The test rejects the probit specification against the semiparametric models.

In line with the literature, differences of the GPG throughout the wage distribution are found. The results suggest glass ceiling and less pronounced sticky floors. Gender wage inequality across the wage distribution is measured by the change in the GPGs across the wage distribution. In this paper, we focus on the 90^{th}, 50^{th} and 10^{th} percentiles. Thus, for the gender wage inequality

[2] Firpo et al. (2009b) despite RIF-OLS propose also RIF-Logit and a fully nonparametric estimator RIF-NP.
[3] Contrary to the approach by e.g. Machado and Mata (2005).

measure, we estimate the 90-10, 90-50 and 50-10 wage gaps.[4] Despite measuring wage inequality between men and women using the change of the GPG at different quantiles, estimation of the variance or gini is also possible (see for example Fortin et al., 2011). The present work focuses on the difference between quantile-specific wage gaps as the phenomena of glass ceiling and sticky floors are particularly relevant when studying gender pay differences across the wage distribution. Indeed, they have been heavily discussed in the literature (Albrecht et al., 2003; Arulampalam, 2007; Xiu and Gunderson, 2014; Cardoso et al., 2016). The detailed decomposition reveals that different categories of covariates such as educational attainment, labor market characteristics or socio-demographic characteristics contribute in distinct ways to the gender gaps at as well as to the change of the gaps between different quantiles. Similarly, the respective categories contribute differently to the explained (endowments effect) or unexplained part (coefficients effect) of the respective pay gaps. The results show that selection effects explain a substantial part of the GPG that would otherwise remain unobserved or be attributed to discrimination. Moreover, the contribution of the selection component to the GPG varies across the wage distribution. The selection-corrected decomposition suggests that sample selection substantially contributes to gender differences in pay along the earnings distribution.

The major contribution of this paper is the extension of the method proposed by Firpo et al. (2009b) to control for sample selection bias and secondly the empirical application of the method to Italy. The paper is organized as follows. In Section 2, the estimation strategy is presented. Section 3 outlines the model extension allowing for sample selection. Section 4 describes the data set used in the analysis and provides the empirical results. Section 5 concludes.

2 Estimation Strategy

The decomposition proposed by Oaxaca (1973) and Blinder (1973) is very popular when it comes to analyzing mean wage differences by groups. In fact, the Oaxaca-Blinder decomposition has become one of the work horses in applied economics (Fortin et al., 2011). Using assumptions of linearity and zero-conditional mean, the approach allows to decompose pay gaps between groups in detail. The method is relatively easy to implement and estimated via OLS. However, the method allows only the estimation at the mean.[5] In the literature, various extensions have been proposed in order to be able to decompose the GPG beyond the mean (e.g Juhn et al., 1993; Donald et al., 2000; Machado and Mata, 2005). The majority of the literature focuses on Conditional Quantile Regressions models (e.g. Buchinsky, 1998; Machado and Mata, 2005). Several of these approaches calculate the aggregate decomposition only and rely on various assumptions as well as are computationally intense. The latter is in particular an issue of the detailed (and not for the aggregate decomposition) beyond the mean. The method proposed by Machado

[4]For example, the 90-10 wage gap is the difference between the GPG at the 90^{th} and the GPG at the 10^{th} percentile.

[5]The Oaxaca (1973) and Blinder (1973) decomposition is outlined in detail in Appendix A.

and Mata (2005) that is reconsidered or applied inter alia by Albrecht et al. (2003) and Melly (2005b, 2005a) allows to conduct a detailed Oaxaca-Blinder type decomposition beyond the mean.[6] The approach is based on CQRs and assigns to the decomposition the effect of each single covariate for a distributional statistic (quantile, variance or gini) other than the mean. However, the method is generally path dependent, i.e. the decomposition outcome depends on the order in which the decomposition is performed (Fortin et al., 2011). In the underlying investigation, UQRs of RIFs are used to obtain a Oaxaca-Blinder type detailed decomposition beyond the mean (Firpo et al., 2009b). In the RIF-OLS model applied here, similar to the assumptions in the classical Oaxaca-Blinder method and the Machado-Mata approach, linearity is assumed. The method based on RIF regressions is, as well as the standard Oaxaca-Blinder decomposition, path independent in the sense of Gelbach (2016). The main advantage of the UQR model over the CQR model is that it allows for the unconditional mean interpretation. The latter is used in Oaxaca-Blinder decompositions and is particularly interesting for policy evaluation as it estimates the effect of regressors on the entire (unconditional) wage distribution (Borah and Basu, 2013). CQRs analyze effects over the conditional wage distribution and hence are applicable only to subgroups of the target population.[7] In cases of concerns of model misspecification due to nonlinearity, the analysis can be repeated with a semiparametric reweighting scheme.[8] The combination of the RIF-OLS decomposition with a semiparametric reweighting estimator proposed by DiNardo et al. (1996) allows to solve the problem of potential misspecification of the RIF-OLS model if linearity does not hold. The analysis shows only small differences when using the Oaxaca-Blinder type decomposition based on RIF-OLS without or with reweighting. In particular, the specification and reweighting errors are small. In Section 4.3, we illustrate that the decomposition outcome with and without reweighting are similar and that the the specification error due to potential nonlinearity is small. This implies that using the RIF-OLS yields a good estimate of the UQPE.[9] As the main focus of this paper is quantile-specific selection correction and as the estimates do not change significantly in the linear or non-linear model, in the following the estimation approach using RIF-OLS is outlined and then extended to allow for sample selectivity. The paper extends the RIF-OLS model such that it corrects the wage model for selection bias at the corresponding quantile. It is accounted for sample selectivity issues using three distinct binary choice models; probit, Ichimura (1993) and Klein and Spady (1993). Even though, the semiparametric Ichimura and Klein-Spady models are computationally costly, the paper focuses on these models for sample correction as distributional assumptions may be important in sample-selection processes (Martins, 2001; Frölich, 2006). Indeed, a specification

[6] Albrecht et al. (2003) and Melly (2005b, 2005a) use the working paper version of Machado and Mata (2005).

[7] For illustration, we compare estimates of the gender wage penalty obtained from CQRs and UQRs in Section 4.2.

[8] Indeed, if the assumption of linearity in the RIF-OLS does not hold, the model is misspecified. The estimation procedure with reweighting is outlined in Appendix B. The results of the method without and with reweighting are summarized in Section 4.3.

[9] Firpo et al. (2009b) find that RIF-OLS estimates compared to RIF-Logit and the completely nonlinear RIF-NP estimates are very similar for the effect of union membership on log wages.

test rejects the parametric selection model and the semiparametric approaches are found to be, especially at lower quantiles, more informative.[10] Using the proposed extension allows to compute the selection-adjusted quantile-specific Oaxaca-Blinder type decomposition of the GPG showing explicitly the contribution of sample selectivity to the quantile-specific GPGs.

2.1 RIF Regressions at Quantiles

The RIF-OLS regression model allows to estimate the effect of explanatory variables, X, on the unconditional quantile, Q_τ, of an outcome variable, Y. The RIF is estimated in quantile regressions by first calculating the sample quantile $\hat{Q}_\tau$ and computing the density at $\hat{Q}_\tau$, that is $f(\hat{Q}_\tau)$ using kernel methods (Firpo et al., 2009b). Moreover, this approach relies on the indicator function $\mathbb{1}\{Y \leq Q_\tau\}$ taking value one if the condition in $\{\cdot\}$ is true, zero otherwise. Estimates for each observation i of the RIF, $\widehat{RIF}(Y_i; Q_\tau)$, are then obtained by inserting $\hat{Q}_\tau$ and $f(\hat{Q}_\tau)$ in the aggregate RIF-function, defined as:

$$\begin{aligned} RIF(Y; Q_\tau) &= Q_\tau + IF(Y; Q_\tau) \\ &= Q_\tau + \frac{\tau - \mathbb{1}\{Y \leq Q_\tau\}}{f_Y(Q_\tau)} \\ &= \frac{1}{f_Y(Q_\tau)}\mathbb{1}\{Y > Q_\tau\} + Q_\tau - \frac{1}{f_Y(Q_\tau)}(1-\tau) \end{aligned} \tag{1}$$

where the RIF is the first order approximation of the quantile Q_τ. $IF(Y; Q_\tau)$ represents the influence function for the τth quantile. It measures the influence of an individual observation on the τth quantile. Adding the quantile Q_τ to the influence function yields the RIF. The probability density of Y evaluated at Q_τ is $f_Y(Q_\tau)$.

Firpo et al. (2009b) model the conditional expectation of the RIF-regression function, $E[RIF(Y; Q_\tau)|X]$, as a function of explanatory variables, X, in the UQR:

$$E[RIF(Y; Q_\tau)|X] = g_{Q_\tau}(X) \tag{2}$$

where a linear function $X\beta_\tau$ is specified for $g_{Q\tau}(X)$, as for example in Borah and Basu (2013). The average derivative of the UQR, $E_X\left[\frac{dg_{Q_\tau}(X)}{dX}\right]$, captures the marginal effect of a small location shift in the distribution of covariates on the τth unconditional quantile of Y keeping everything else constant. Therefore, the coefficients, β_τ, can be unconditionally interpreted, as $E[RIF(Y; Q_\tau)] = E_X\big[E\big(RIF(Y; Q_\tau)|X\big)\big] = E(X)\beta_\tau$. That is the unconditional expectations $E[RIF(Y; Q_\tau)]$ using the LIE allow for the unconditional mean interpretation. On the contrary, only the conditional mean interpretation is valid in the context of CQRs; $Q_\tau(Y|X) = X\beta_\tau^{CQR}$, where β_τ^{CQR} can be interpreted as the effect of X on the τth conditional quantile of Y given X. The LIE does not apply here; $Q_\tau \neq E_X[Q_\tau(Y|X)] = E(X)\beta_\tau^{CQR}$, where Q_τ is the unconditional quantile. Hence, β_τ^{CQR} cannot be interpreted as the effect of increasing the mean value

[10]The specification test is outlined in Section 4.4.1.

of X in the unconditional quantile Q_τ. This is one pitfall of CQRs in decomposition methods. The unconditional mean interpretation is important for decompositions in the sense of Oaxaca (1973) and Blinder (1973). Indeed, Oaxaca-Blinder decompositions use the unconditional mean interpretation of β_τ, i.e. the interpretation of β_τ as the effect of increasing the mean value of X on the mean value of Y. In UQR, the coefficients β_τ can thus be estimated by OLS in the following way:

$$Q_\tau = E[RIF(Y;Q_\tau)] = E_X[RIF(Y;Q_\tau)|X] = E(X)\beta_\tau \tag{3}$$

The basic wage equation of the RIF-OLS model at quantile τ, with $\tau \in (0,1)$, is then:

$$RIF(Y;Q_\tau) = X\beta_\tau + u_\tau \tag{4}$$

where Y is the natural logarithm of hourly earnings and X is a vector of K explanatory variables (including the constant), β_τ is the corresponding coefficient vector and u_τ is the corresponding error term. The coefficient vector of the unconditional quantile at each observation i is defined as:

$$\hat{\beta}_\tau = (\sum_{i=1}^{N} X_i' X_i)^{-1} \sum_{i=1}^{N} X_i' \widehat{RIF}(Y_i;Q_\tau) \tag{5}$$

UQRs estimate the effect of covariates on all parts of the earnings distribution and are thus particularly interesting for policy implications or evaluation. CQRs do not allow to draw conclusions about the impact of a variable on the overall earnings distribution but rather provide insights about the dispersion of earnings within different subgroups of the target population (Borah and Basu, 2013).

2.2 Decomposition

Given the assumptions that the mean of the RIF-function is equal to the actual quantile as well as to the mean of the conditional expectation given X shown in equation (3), we have:

$$\begin{aligned} E[RIF(Y_M;Q_\tau)|X_M] - E[RIF(Y_F;Q_\tau)|X_F] &= \bar{X}_M\beta_{M\tau} - \bar{X}_F\beta_{F\tau} \\ &= \Delta_\tau \end{aligned}$$

where $\hat{\Delta}_\tau$ is the GPG at the τth quantile and $M = \textit{Male}$ and $F = \textit{Female}$.

The GPG is, as in the standard two-fold Oaxaca-Blinder decomposition, decomposed in an endowments (explained) and a coefficients (unexplained) component. The decomposition has then the following form:

$$
\begin{aligned}
\hat{\Delta}_\tau &= \hat{\Delta}_{E\tau} + \hat{\Delta}_{C\tau} \\
&= (\bar{X}_M - \bar{X}_F)\hat{\beta}_{F,\tau} + \bar{X}_M(\hat{\beta}_{M,\tau} - \hat{\beta}_{F,\tau})
\end{aligned} \tag{6}
$$

where the index E indicates the *Endowments Effect* and the index C the *Coefficients Effect*.

To perform a detailed decomposition, the contribution of each element of the vector of explanatory variables $\bar{X}$ on both components is estimated. For identification, a detailed decomposition underlies thus stronger assumptions such as functional form restrictions as well as potentially further restrictions on the distribution of the error term. An example is the assumption of independence of the set of covariates and the dummy identifying group membership (Fortin et al., 2011). In the RIF-OLS model, the detailed components can be estimated in the same way as in the detailed Oaxaca-Blinder decomposition at the mean. However, as in the Oaxaca-Blinder decomposition at the mean, the decomposition based on RIF-OLS changes according to the choice of the reference category (Reimers, 1983; Cotton, 1988; Neumark, 1988; Oaxaca and Ransom, 1994). We follow the standard case and use male coefficients as the non-discriminatory wage structure. As in standard detailed Oaxaca-Blinder decompositions at the mean, the contribution of the single regressors to the components of the GPG are path independent also in the RIF-OLS framework.

3 Accounting for Selection

The estimation strategy outlined in Section 2.1 yields inconsistent and biased estimates of the wage equation and hence of the decomposition parts due to non-randomness of the sample (Heckman, 1979; 1990; Buchinsky, 1998; Albrecht et al., 2009). Indeed, the observed individuals with a positive labor income may be a non-random subsample of the individuals in the population. As the origin of the selection could be related to earnings, it is essential to explicitly consider the selection process in the estimation of the wage equation. The selection into wage work may depend on some positive factors such as individual ability, motivation or educational quality, raising both, the probability of being employed and wages. However, it is omitted in the earnings equation as these factors are unobservable in the data. The incidence of receiving a wage offer may not only be non-random but also different for men and women. Using the proposed extension of the quantile-specific wage model allows to obtain consistent estimates as well as to attribute the selection effect to the endowments and coefficients part of the quantile-specific GPGs. The estimation procedure consists, similar to Heckman (1979), of two steps. In a first-step estimation, the semiparametric estimator of the selection parameter is estimated. In a second-step regression, the selectivity-corrected model is estimated. The main difference compared to Heckman (1979) is that here the estimated selection terms are estimated with distribution-free approaches rather than by a parametric method (Newey, 2009). Moreover, instead of using only the traditional IMR, an approximation function is used.

The selection decision of interest is the employees' work decision. The decision is identified by the indicator variable E, which is equal to one if the individual is in employment and zero otherwise. The reservation wage, Y^{res}, is not observed but we observe, whether the difference between the market wage, Y, and Y^{res} is positive or not. Hence, $E = 1$ if $Y - Y^{res} > 0$, $E = 0$ otherwise. In a first-step estimation, the selection equation of the single-index model is estimated with SLS and reads as:[11]

$$E = m(Z\gamma) + v \tag{7}$$

where Z is a $1 \times T$ vector of regressors influencing the employment decision with $t = 0, \ldots, T$. The corresponding parameters are contained in the $T \times 1$ column vector γ and v is the usual additive error term, which is assumed to be uncorrelated with Z. The function $m(\cdot)$ is an unknown link or smooth function. Contrary to parametric models, in semiparametric single-index models, not only γ but also $m(\cdot)$ must be estimated.[12] The set of covariates Z includes at least one variable not included in X and uncorrelated with the log of hourly wages Y (the underlying dependent variable) but influencing the work decision. This is important for identification of the selection decision. Moreover, if the regressors in Z are not different from the variables in X, the selectivity-corrected regression will be highly collinear. Semiparametric single-index models (such as the Ichimura and Klein-Spady model) are quite popular in nonparametric estimation as they work similar to parametric models (Henderson and Parmeter, 2015). However, no distributional assumptions are required to set up these models, while in the probit model, the standard normal distribution is assumed. Using the semiparametric single-index models that do not require any distributional assumptions allows to circumvent potential bias of the selection-correction terms due to non-normality of the selection process. Indeed, distributional assumptions may be important when considering sample-selection processes (Martins, 2001).

The semiparametric single-index models used to estimate the selection equation are iterative procedures and hence are computationally heavy given that nonparametric kernel estimation is conducted at each iteration. For the estimation, the second-order Gaussian kernel is used and the bandwidth is selected by likelihood cross-validation. The SLS estimator is consistent and independent of the distribution of v (Buchinsky, 1998). The Klein-Spady model achieves the semiparametric efficiency bound for binary choice models, while the Ichimura estimator is inefficient if the model suffers from heteroskedasticity (Ichimura, 1993).[13] Buchinsky (1998), as well as Albrecht et al. (2009) and Chzhen and Mumford (2011) use power series estimation

[11] The parametric selection equation has the following form: $E = Z\gamma + v$.

[12] The general form of single-index models is: $E = m(\phi(Z, \gamma)) + v$, where $m(\cdot)$ is the unknown smooth function and $\phi(\cdot)$ is a known parametric function with T regressors, and coefficient vector γ having dimension $P \times 1$ (Ichimura, 1993; Henderson and Parmeter, 2015). As $\phi(Z, \gamma)$ is a scalar, it is necessarily single index. Similar to many other studies, we assume a linear single-index, and thus the number of regressors and parameters are equal, i.e. $T = P$.

[13] The probit estimate is efficient under normally distributed errors e.g. Buchinsky (1998).

in order to estimate the correction term in the CQR model. We replace the power series by polynomials of order j.[14] The following polynomial of order j is estimated:

$$\hat{h}_\tau(\hat{m}) = \hat{\delta}_\tau PS(\hat{m}) \tag{8}$$

where $PS(\hat{m})$ is a polynomial vector in m:

$$PS(\hat{m}) = \Big[PS_1(\hat{m}), \ldots, PS_J(\hat{m})\Big]$$

and $PS_j(\hat{m}) = \lambda(Z_A\hat{\gamma})^j$ with $j = 1, 2, \ldots, J$. The correction term $\hat{h}_\tau(\hat{m})$ is an approximation of the unknown function for selection correction; $\hat{h}_\tau(\hat{m}) \to h_\tau(m)$ as the number of parameters goes to infinity. The nonlinear function λ is the standard IMR[15] and $\hat{\delta}$ are the corresponding coefficient estimates, which vary with the specific quantile τ. The index A denotes individuals accepting a wage offer. The parameter estimates $\hat{\gamma}$ are estimated via semiparametric single-index methods (Ichimura and Klein-Spady). The correction was shown to be asymptotically normal (Newey, 2009). In this study second-order polynomials are used as polynomials allow for more flexibility than standard parametric selection models (Carneiro et al., 2011; Cornelissen et al., 2016). Even though, second-order polynomials rule out a nonmonotonic shape of $\hat{h}(\cdot)$, we focus on polynomials of order two as higher order polynomials may become instable at the boundaries of the data space (Harrell, 2015).

Estimation of semiparametric selection models in the way described above does not allow for identification of the level of the constant and the first reported continuous variable (Buchinsky, 1998).[16] Therefore, we normalize the respective coefficients from the semiparametric single-index estimations to the corresponding parameter estimates obtained from the probit model.[17] This way of normalizing the coefficients allows also for a better comparison of the Ichimura and Klein-Spady estimation outcome with the probit estimation outcome (Albrecht et al., 2009; Chzhen and Mumford, 2011). We estimate then the following expression:

$$\hat{h}^*_\tau(\hat{m}^*) = PS(\hat{m}^*) \tag{9}$$

where $PS_j(\hat{m}^*) = \hat{\delta}^*_\tau\lambda^*(Z^*_A\gamma^*)^j$ with $Z^*_A = (1, Z_{A,1}, Z_{A,T-2})$ and $\hat{\gamma}^* = (\hat{\gamma}^*_0, \hat{\gamma}^*_1, \hat{\gamma}_{T-2})^T$ having dimension $1 \times (1 + 1 + T - 2)$ include the normalized constant $\hat{\gamma}^*_0$ as well as the normalized coefficient estimate of the first continuous variable $\hat{\gamma}^*_1$ from the selection decision. The coefficient vector $\hat{\gamma}_{T-2}$ includes all the remaining parameter estimates from the single-index models. The vector $Z^*_A\hat{\gamma}^*$ has then dimension 1×1. The (nonlinear) function or the IMR, $\lambda^*(Z^*_A\hat{\gamma}^*)$, is estimated and depends on the normalized constant, the normalized coefficient estimate of the

[14] Using orthogonal polynomials allows to rule out multicollinearity issues (see Newey, 2009, for further details).

[15] with $\lambda = \frac{\phi(\cdot)}{\Phi(\cdot)}$ being the usual IMR; $\phi(\cdot)$ is the probability density function, $\Phi(\cdot)$ the cumulative distribution function.

[16] The semiparametric estimators require scale and local normalization (Buchinsky, 1998; Newey, 2009).

[17] For an overview of normalization in single-index models see for example Cameron and Trivedi (2009).

first continuous variable in Z as as well as on the other variables in Z and has dimension 1×1, $\hat{\delta}^*$contains the corresponding coefficient estimates.

In the second-step estimation, the function for selection correction $\hat{h}^*_\tau(\cdot)$ is included in the basic wage equation, i.e. equation (4), correcting for selection at the τth quantile. Thereby, $\hat{h}^*_\tau(\cdot)$ acts as the IMR does in the Heckman (1979) two-step procedure but is quantile-specific and does not require any distributional assumptions of the error terms of the selection process. The wage equation corrected for selectivity bias at the τth quantile with $j = 2$ looks as follows:

$$\begin{aligned}\widehat{RIF}(Y; Q_\tau) &= X\hat{\beta}_\tau + \hat{h}^*_\tau(\hat{m}^*) + \hat{\epsilon}_\tau \\ &= X\hat{\beta}_\tau + \hat{\delta}^*_\tau PS(\hat{m}^*) + \hat{\epsilon}_\tau \\ &= X\hat{\beta}_\tau + \hat{\delta}^*_{1\tau}\lambda^*(Z^*_A\hat{\gamma}^*)^1 + \hat{\delta}^*_{2\tau}\lambda^*(Z^*_A\hat{\gamma}^*)^2 + \hat{\epsilon}_\tau \end{aligned} \tag{10}$$

where Y is the natural logarithm of hourly earnings and X is a vector of K explanatory variables, the selection correction term $\lambda^*(Z^*_A\hat{\gamma}^*)^j$ is a function evaluated at $Z^*_A\hat{\gamma}^*$. The corresponding coefficient vectors are $\hat{\beta}_\tau$ and $\hat{\delta}^*_{j\tau}$ with $j = 1, 2$. For equation (10) to hold, the following assumptions are made. The reservation and the market wage depend on unobservables, the joint distribution of u and v is continuous and the probability of observing a positive difference $(Y - Y^{res})$ given Z, depends only on $Z\gamma$.[18] The selectivity-corrected coefficient estimates are consistent and asymptotically normal distributed. This holds under the assumption that the second-stage estimation successfully corrects for the selection bias (see Appendix C for further details). The consistent coefficient estimates are then obtained from RIF-OLS regression of $\widehat{RIF}(Y; Q_\tau)$ on X, $\lambda^*(Z^*_A\hat{\gamma}^*)^1$ and $\lambda^*(Z^*_A\hat{\gamma}^*)^2$.

The parametric selection correction is conducted as in the standard OLS model adjusted for sample selectivity, i.e. the IMR is added as a regressor to the earnings equation (Heckman, 1979). The RIF-OLS model with parametric selection correction is presented in Appendix D.

4 Empirical Application

4.1 Data and Descriptive Statistics

The empirical analysis is based on the survey Plus[19] from the Italian Isfol. The survey is particularly relevant for the study of wage inequality by gender as it delivers broad information on the personal working profiles and individual motivation of the interviewees.

The underlying study uses the complete release of panel dimension.[20] The estimation is based on a pooled regression model including wave or year dummies as explanatory variables. Individuals enter as well as leave the sample (through attrition). Hence, the composition of the sample changes. The analysis is restricted to the private sector only as there has been a

[18]Similar to the assumptions made by Buchinsky (1998) for sample correction in CQRs.
[19]PLUS = Participation, Labor, Unemployment Survey
[20]Up to now, ISFOL PLUS has released the following data waves; 2005, 2006, 2008, 2010, 2011, 2014.

general 'wage freeze' in the Italian public sector at the beginning of the 21$^{\text{st}}$ century (Bordogna, 2012; Piazzalunga and Di Tommaso, 2015). This policy disproportionately affected women as women are more likely to work in the public sector. Consequently, the policy influenced the GPG. The analysis focuses on employees working at least 15 and maximally 45 hours per week. Self-employed, students, pensioners as well as other inactive and involuntarily unemployed individuals are excluded from the analysis. The selection decision of interest is thus the employment or work decision from search or voluntary unemployment. We consider only labor income from the main job (defined as the job that pays the highest wage). After deleting observations with missing values on other variables of interest, we are left with a sample size of 24,267 individual wage observations in the private sector[21], of which 11,390 are female and 12,877 are male. This study uses the log of hourly wage as dependent variable. It is defined as the net monthly wage perceived divided by the number of actual working hours. An alternative are monthly gross earnings, which, however, are almost entirely missing (98% of all observations are missing). As a second alternative, gross annual earnings could be used. However, dividing gross annual earnings by the number of months in a calendar year (plus an additional 13$^{\text{th}}$ month), gives a difference amounting on average to more than 800 Euros per month between the artificially created monthly gross income and the reported monthly gross income. Therefore, we prefer to use the monthly-based net income as dependent variable. Individuals with children are granted tax credits in Italy.[22] As the tax credit is granted yearly, it does not impact on the monthly perceived net income and hence having children does not directly affect monthly perceived net wages in Italy. The explanatory variables used in the regression analysis are grouped in the following categories: *Education*, *Experience*, *Job Characteristics*, *Occupations and Industries*, *Socio-Demographic Background* and *Selection*. The set of regressors labeled *Education* contains variables controlling for the level of educational attainment as well as for excellence in education. The category *Experience* includes labor market experience and labor market experience squared as well as job tenure. *Job Characteristics* include job-specific variables such as wage compensatings (the level of satisfaction with the working climate, with work place stability, with the working time as well as with the tasks at the current job). These job characteristics influence the level of (net hourly) wages as employers offering lower wages, may compensate their employees with more satisfactory job characteristics (Filer, 1985). Additionally, dummies controlling for the kind of contract (part-time and unlimited) are included. The set of explanatory variables *Occupations and Industries* contains sectoral and occupational dummies, while the category *Socio-Demographic Background* contains geographic controls as well as a dummy accounting for whether the individual holds the Italian citizenship. The category controls also for the family status (married or not) and the educational background of the parents (whether

[21] 17,798 observations of the public sector have been dropped. The sample initially consists of 159,615 observations in total.

[22] In order to be eligible to the grant, annual gross earnings need to be below 95,000 Euro (see Worldwide-Tax-Summaries, 2017, for further information).

they have graduated from university). This category controls for any potential labor-market favoritism or discrimination coming from informal social networks. Indeed, informal networks may be important in Italy and may directly influence the wage level (Pistaferri, 1999).[23] Time-varying characteristics are caught by wave dummies and are included in this category.[24] The category *Selection* contains the selection correction terms. A complete list of variables used in the study along with their categories and definitions can be found in Appendix E, Table E.1.

Table 1 reports means and standard deviations for some of the variables included in the analysis. Women have on average higher educational attainment than men, while men have more years of labor market experience (*Exper*) and work on average longer for the same firm (*Tenure*) than women. The underlying sample shows no huge differences in the level of satisfaction with particular job characteristics between men and women. However, differences in the type of contract are found. Women have much more often than men a part-time contract, while male employees have more often an unlimited contract than female employees. There are no significant differences in geographic indicators between women and men (*North* and *Centre)*. Most of the individuals observed are Italian citizens (*Italian*). Men and women are relatively equal in terms of marriage (*Married*) as well as in having children at all (*Kids*). Yet, female employees have more often children with less than ten years (*Kids_10*) compared to male employees. Female workers engaged in the labor market are about four years younger than male employees (*Age*). The variables *Age*, *Kids* and *Kids_10* are included in the selection equation only.

[23]Individuals with access to these networks are more likely to obtain more attractive and thus generally better-paying jobs.

[24]If not stated differently, the category *Occupations and Industries* contains sectoral dummies and the category *Socio-Demographic Background* contains year or wave dummies.

Table 1: Descriptive Statistics

	(1)	(2)	(3)	(4)
	Women		Men	
	Mean	Std.Dev.	Mean	Std.Dev.
Education				
Elementary_School	0.015	0.120	0.016	0.127
High_School	0.584	0.493	0.590	0.492
University_Degree	0.251	0.433	0.165	0.371
Max_D_Mark	0.039	0.194	0.020	0.139
Experience				
Exper	13.942	11.307	17.813	13.396
Tenure	8.380	8.861	11.992	11.636
Job Characteristics				
Work_Climate	3.079	0.852	3.055	0.825
Work_Stab	2.937	0.982	2.985	0.949
Work_Time	3.022	0.849	3.021	0.806
Work_Task	3.043	0.777	3.009	0.771
Part	0.251	0.434	0.054	0.227
Contract_Type	0.761	0.426	0.818	0.386
Occupations and Industries				
Manager	0.111	0.314	0.111	0.314
Intermed Prof	0.555	0.497	0.405	0.491
Socio-Demographic Background				
North	0.554	0.497	0.522	0.500
Centre	0.211	0.408	0.198	0.398
Italian	0.988	0.110	0.995	0.074
Married	0.480	0.500	0.446	0.497
Age	34.920	10.508	37.866	12.901
Kids	0.481	0.500	0.461	0.498
Kids_10	0.300	0.458	0.230	0.421
Observations	11,390		12,877	

4.2 The Effect of Women on Earnings and Raw GPGs

It is a well-known result in the literature that women perceive lower wages than men – other things equal e.g. Blau and Kahn (1992, 2003); England (2006); Grove et al. (2011). Table 2 shows the unadjusted GPG at the mean and at different quantiles (Panel A) as well as the 90-10, 90-50 and 50-10 wage gap (Panel B). The raw mean GPG in log hourly wages in the underlying sample amounts to 11.8 percentage points. Arulampalam et al. (2007) find for the Italian private sector in the period 1995-2001 a mean wage gap between men and women equal to 15.3 percentage points. They find a GPG amounting to 14.5 percentage points at the 10th percentile, to 13.0 percentage points at the 50th percentile and to 19.4 percentage points at the 90th percentile.[25] In the underlying sample quantile-specific GPGs are equal to 11.7, 10.0 and 17.9 percentage points at the 10th, 50th and 90th percentile, respectively. Glass ceiling and sticky floors are assumed to exist in an economy, when the 90th and 10th percentile GPG, respectively, exceeds the reference percentile wage gap by at least two percentage points (e.g. Arulampalam et al., 2007). Indeed, Table 2 shows that class ceiling is found in the underlying study for the Italian private sector; the 90th percentile wage gap exceeds the 10th percentile GPG by 6.2 percentage points and the 90th percentile wage gap exceeds the median pay gap by almost 8 percentage points. The 10th percentile pay gap lies slightly above the 50th pay gap (the 50-10 wage gap is slightly negative). As the 50-10 wage gap is slightly lower than 2 percentage points (in absolute terms), only weak evidence for sticky floors is found. This result is in line with the finding of Arulampalam et al. (2007) finding a 50-10 wage gap of -1.9 percentage points for the Italian private sector. Hence, the pay gap between men and women varies significantly between the top and bottom or median and the bottom and median of the wage distribution. Yet, in the latter case, the difference is less pronounced. This finding underlines the importance of considering the GPG at different quantiles and not only at the mean. Indeed, policy implications may change according to whether the gap at different quantiles or at the mean is considered. In particular, not only the magnitude of the raw GPG but also the decomposition may vary across the wage distribution. Similarly, selection effects may change across the distribution. Even when assuming that men and women have the same set of observable labor market characteristics, i.e. considering the unexplained component[26], there is a substantial (adjusted) GPG at the mean as well as along the wage distribution due to differences in returns to observable labor market characteristics (see Table 2, Panel A).[27] This implies that the Italian private sector suffers from a wage gap that is mainly due to the unexplained component, also referred to as discrimination. Even though the coefficients component, i.e. the portion of the GPG not due to gender differences in observed characteristics, is generally taken to be an estimate of gender discrimination, the

[25] Eurostat finds for the period considered in this study (2005-2014) an average raw GPG in hourly wages equal to 5.6% for Italy as a whole, i.e. for the public and private sector (Eurostat, 2017).

[26] Following the standard set-up of the Oaxaca-Blinder decomposition, the female set of labor market characteristic, $\bar{X}_F$, is used.

[27] The full estimation outcome from the standard decomposition at the mean is shown in Table A.1, while the regression output from the RIF-OLS decomposition is presented in Table 4.

unexplained portion of the GPG may include effects of unobserved productivity, innate ability or other unobserved characteristics (Blau and Kahn, 2006). Hence, the unexplained component or adjusted GPG may change, when it is accounted for sample selection.

Table 2: GPG at Different Quantiles and across the Wage Distribution

(a) Panel A: GPG at the Mean and at Different Quantiles

	(1)	(2)	(3)	(4)
	Mean	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
GPG	0.118***	0.117***	0.100***	0.179***
(Unadjusted Gap)	(0.005)	(0.010)	(0.004)	(0.009)
Adjusted GPG	0.124***	0.115***	0.097***	0.160***
	(0.006)	(0.010)	(0.004)	(0.009)

Bootstrapped standard errors in parentheses, 100 replications

$***p < 0.01, **p < 0.05, *p < 0.1$

Notes: The unadjusted GPG is equal in magnitude to the raw GPG. The adjusted GPG is the unexplained or coefficients part of the decomposition. The wage gaps have been estimated using the decomposition model outlined in Section 2.2.

(b) Panel B: GPG across the Wage Distribution

	(1)	(2)	(3)
	90-10	90-50	50-10
Unadjusted Change	0.062***	0.079***	-0.018***
	(0.011)	(0.009)	(0.008)

Bootstrapped standard errors in parentheses, 100 replications

$***p < 0.01, **p < 0.05, *p < 0.1$

Notes: The unadjusted change is the change in the unadjusted GPG from the top to the bottom and median, column (1) and (2), as well as from the median to the bottom quantile, column (3).

Table 3 reports coefficient estimates for the dummy variable *female* of a Mincer-type wage model for the 10^{th}, 50^{th} and 90^{th} percentile using standard OLS, RIF-OLS and CQR.[28] The effect of being a women is, as expected, strictly negative all along the wage distribution as well as at the mean. According to the OLS estimate, for female employees earnings are reduced by approximately 11.5 percentage points. The UQR and CQR show as well that being a women decreases earnings in the corresponding quantile of the conditional or unconditional earnings distribution. The unconditional (negative) effect of women on log hourly earnings decreases in absolute terms from the bottom to the median and increases thereinafter sharply. The conditional effect decreases slightly from the 10^{th} to the 50^{th} percentile and increases thereafter. Figure 1 plots the effect of being female on log hourly wages for both quantile methods.[29] The partial effect from the UQR is highly nonmonotonic, while the partial effect from the CQR shows almost a linear pattern from the 20^{th} percentile onwards. Both, Table 3 and Figure 1 show that the magnitude of the estimation results changes depending on which approach (UQR or CQR) is used.

Table 3: OLS, UQR and CQR of Log Hourly Wages – Gender Wage Penalty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		10^{th} Percentile		50^{th} Percentile		90^{th} Percentile	
	OLS	UQR	CQR	UQR	CQR	UQR	CQR
female	-0.122***	-0.115***	-0.117***	-0.106***	-0.112***	-0.181***	-0.150***
	(0.005)	(0.012)	(0.007)	(0.005)	(0.004)	(0.012)	(0.009)
Sectoral Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses for OLS
Bootstrapped standard errors in parentheses, 100 replications, for UQR and CQR

In the following, the detailed decomposition results at specific quantiles as well as across the wage distribution using the 90-10, 90-50 and 50-10 wage gaps as inequality measures are presented. Then, the estimation results from the parametric and semiparametric binary choice models are outlined and the set-up of the test for equality of the parametric and semiparametric models as well as the results from the test are discussed. Finally, the decomposition outcome with selection adjustment is shown.

[28] The full regression output of the Mincer-type wage model using OLS, UQR and CQR, respectively, is shown in Appendix F, Table F.1. For all three model specifications, the same set of regressors is used.

[29] The CQ and UQ partial effects are evaluated at the 0.05, 0.1, 0.15,. . .,0.90, 0.95 quantile, respectively.

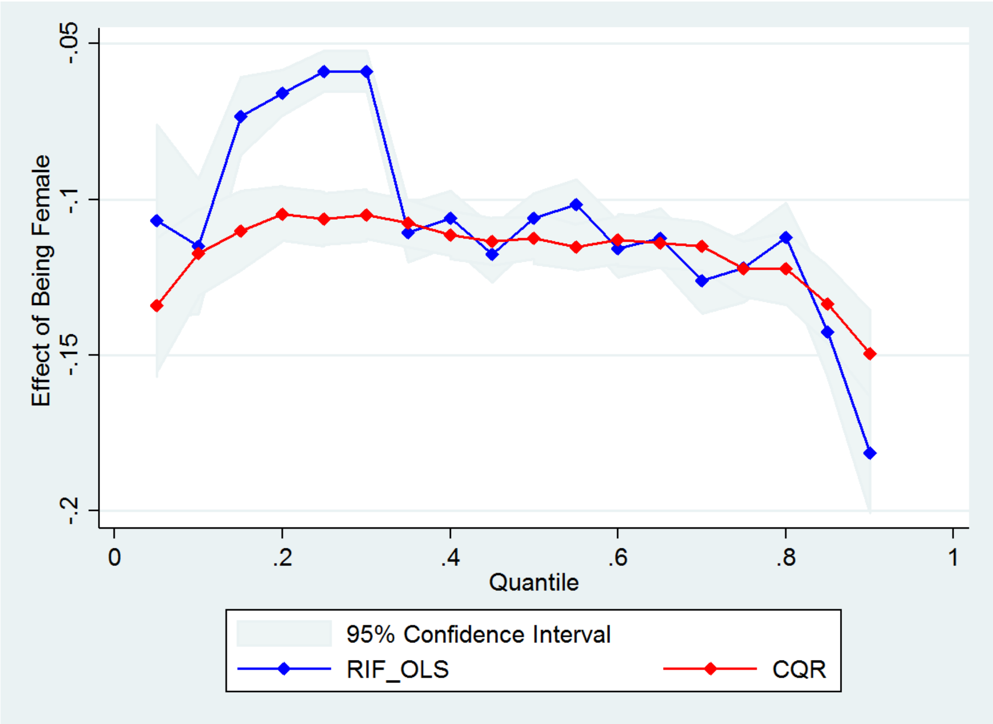

Figure 1: UQR and CQR Estimates of the Effect of Women on Log Hourly Wages

4.3 RIF-OLS Decomposition along the Wage Distribution without Selection Adjustment

Table 4 shows the decomposition outcome at specific quantiles. Women are found to have higher observable educational characteristics than men. The difference between men and women is highest at the top of the wage distribution. On the contrary, male employees have higher experience and job tenure. Again, the difference is highest at the 90^{th} percentile. Differences in job characteristics as well as in occupations and industries are insignificant at the bottom but negative at the median and top of the wage distribution. The endowments effect of socio-demographic background characteristics reduces the GPG slightly all along the wage distribution. Hence, employed women generally are more often located in the North or Centre of Italy, come from families with higher educational background and are more often married compared to men. The total explained part is positive for low-income earners but negative for median- and top-income earners. However, differences in observable labor market characteristics between men and women statistically significantly reduce only the 90^{th} percentile GPG. In terms of the coefficients effect, educational differences between men and women are insignificant at the bottom, negative at the median and positive at the top of the wage distribution. Gender differences in coefficients to experience and job tenure are positive throughout the wage distribution. Different remuneration to job characteristics between men and women significantly raises the GPG only at the 90^{th} percentile. Gender-specific distributional differences in specific occupations or industries have a statistically significant impact on the coefficients effect all along the wage distribution. Occupational and industrial gender differences in coefficients are negative at the bottom but positive at the median and top of the wage distribution. An intuition of the negative coefficient effect due to distributional differences in occupations and industries between men and women at the 10^{th} percentile GPG is that women are relatively more likely to self-select themselves in low-income jobs and hence to receive the adequate formal education for these jobs e.g. Brekke and Nyborg (2010). On the contrary, men working in the corresponding sector or occupation at the bottom of the wage distribution have higher probability of not having the adequate formal training compared to their female colleagues. The consequences are negative coefficient effects due to distributional differences in occupations and industries. Negative coefficient estimates due to gender differences in occupations and industries at the bottom of the wage distribution are also found by other studies (e.g. Xiu and Gunderson, 2014). The coefficients effect of socio-demographic background characteristics is generally insignificant all along the income distribution. Consequently, no evidence for gender-based discrimination or favoritism in the labor market based on informal networks is found in this study. The total unexplained part is statistically significant and positive throughout the distribution. In particular, it is a main driver of the GPG at all quantiles considered, while the total explained part is rather small or even working towards a closure of the gap. The coefficient component includes the constant term.[30]

Table 5 shows the detailed decomposition results of the different wage inequality measures (90-10, 90-50 and 50-10, respectively). By looking at the different components of the inequality measures in terms of the endowments effect, gender differences in educational attainment is found to reduce wage inequality between the top and bottom or median of the wage distribution. Statistically significant and positive endowments effects of experience and tenure are found for the top-bottom and top-median wage gaps. Hence, in terms of the explained component gender differences in labor market experience and job tenure increase the 90-10 and 90-50 wage gaps, respectively. Job characteristics as well as occupational and sectoral differences reduce the difference in the GPG across the wage distribution. Differences by gender in socio-demographic characteristics have a relevant but small impact on glass ceiling. All in all, differences in the explained component decrease the difference between the GPGs at the top and bottom or median of the wage distribution. In line with the relatively small 50-10 wage gap, gender differences between the median and bottom of the earnings distribution are found to be rather negligible. By looking at the unexplained component, positive coefficients of education are found to be a main driver of the gender pay disparity between high- and low- or median-income earners. Positive gender differences in returns to experience are found between the 90-10 and 90-50 wage gaps. Similarly, gender differences in job characteristics contribute statistically significantly to the difference between the GPG at the 90^{th} and 10^{th} or 50^{th} percentile. Gender differences in

[30] At the bottom and median there is a premia for simply being male. Contrary, on the top there is a premia for being female.

coefficients due to job- and industry-sorting are another driver of gender wage inequality in the Italian private sector. On the contrary, the coefficients effect due to changes in differences in socio-demographic characteristics between men and women are found to have no statistically significant impact on the 90-10, 90-50 and 50-10 pay gaps. The total unexplained component is an important driver between the pay gaps at the top and bottom or median of the wage distribution.[31]

In Appendix B, the reweighted decomposition approach is outlined and the decomposition outcome with reweighting for both the quantile-specific GPG and the gender wage inequality measures is shown (Tables B.1–B.2). The total reweighting error, $(\bar{X}_M - \bar{X}_M)\hat{\beta}_{\tau}^{rew}$, corresponds to the difference between the *Total Explained* across the UQ Oaxaca-Blinder decomposition and the reweighted-regression decomposition. The reweighting error reflects the fact that the endowments effect in the decomposition with reweighting is not exactly equal to the standard endowments effect, i.e. without reweighting. This occurs, when the reweighted $\bar{X}^{rew}$ is not exactly equal to $\bar{X}$. Figure 2 shows the reweghting error and Figure 3 the specification error graphically along the wage distribution. The (total) specification error is the difference between the *Total Unexplained* component from the model without and with reweighting; $\bar{X}_M^{rew}(\hat{\beta}_{M,\tau} - \hat{\beta}_{M,\tau}^{rew})$. The specification error is zero if the base model is truly linear. Both errors are rather small, therefore, we expect the RIF-OLS model without reweighting not to be misspecified.

[31] As stated before, the wage structure component contains the constant term. Differences in the constant term decrease wage inequality from the top to the bottom.

Table 4: RIF-OLS Detailed Decomposition at Different Quantiles

	(1)	(2)	(3)
	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
GPG (Unadjusted Gap)	0.117***	0.100***	0.179***
	(0.010)	(0.004)	(0.009)
Endowments Effect			
Education	-0.013***	-0.013***	-0.029***
	(0.002)	(0.001)	(0.003)
Experience	0.024***	0.026***	0.066***
	(0.003)	(0.002)	(0.004)
Job Characteristics	0.005	-0.004*	-0.030***
	(0.006)	(0.002)	(0.006)
Occupations and Industries	0.000	-0.001	-0.025***
	(0.004)	(0.002)	(0.006)
Socio-Demographic Background	-0.008***	-0.009***	-0.013***
	(0.002)	(0.001)	(0.002)
Total Explained	0.009	-0.001	-0.031***
	(0.008)	(0.004)	(0.009)
Coefficients Effect			
Education	-0.040	-0.027***	0.102***
	(0.026)	(0.010)	(0.023)
Experience	0.012	0.025**	0.123***
	(0.026)	(0.010)	(0.024)
Job Characteristics	-0.009	0.009	0.114**
	(0.052)	(0.020)	(0.048)
Occupations and Industries	-0.288***	0.052**	0.223***
	(0.070)	(0.026)	(0.062)
Socio-Demographic Background	-0.012	-0.030	-0.059
	(0.111)	(0.043)	(0.110)
Total Unexplained	0.108***	0.100***	0.210***
	(0.012)	(0.005)	(0.012)

Bootstrapped standard errors in parentheses, 100 replications

$***p < 0.01, **p < 0.05, *p < 0.1$

Table 5: Gender Wage Inequality – RIF-OLS Decomposition Results

	(1)	(2)	(3)
	90-10	90-50	50-10
Unadjusted Change	0.062***	0.079***	-0.018**
	(0.011)	(0.009)	(0.008)
Detailed Endowments Effect			
Education	-0.016***	-0.011***	-0.001
	(0.003)	(0.003)	(0.002)
Experience	0.041**	0.039***	0.002
	(0.004)	(0.005)	(0.003)
Job Characteristics	-0.035***	-0.026***	-0.009*
	(0.007)	(0.006)	(0.005)
Occupations and Industries	-0.026***	-0.025***	-0.001
	(0.006)	(0.005)	(0.004)
Socio-Demographic Background	-0.004**	-0.004*	-0.001
	(0.002)	(0.002)	(0.002)
Total Explained	-0.040***	-0.030***	-0.010
	(0.009)	(0.008)	(0.007)
Detailed Coefficients Effect			
Education	0.142***	0.128***	0.014
	(0.027)	(0.023)	(0.020)
Experience	0.111***	0.098***	0.013
	(0.027)	(0.023)	(0.020)
Job Characteristics	0.123**	0.106**	0.017
	(0.056)	(0.048)	(0.041)
Occupations and Industries	0.511***	0.172***	0.340***
	(0.071)	(0.061)	(0.052)
Socio-Demographic Background	-0.047	-0.029	-0.018
	(0.127)	(0.109)	(0.092)
Total Unexplained	0.102***	0.110***	-0.008
	(0.013)	(0.011)	(0.010)

Bootstrapped standard errors in parentheses, 100 replications

$***p < 0.01, **p < 0.05, *p < 0.1$

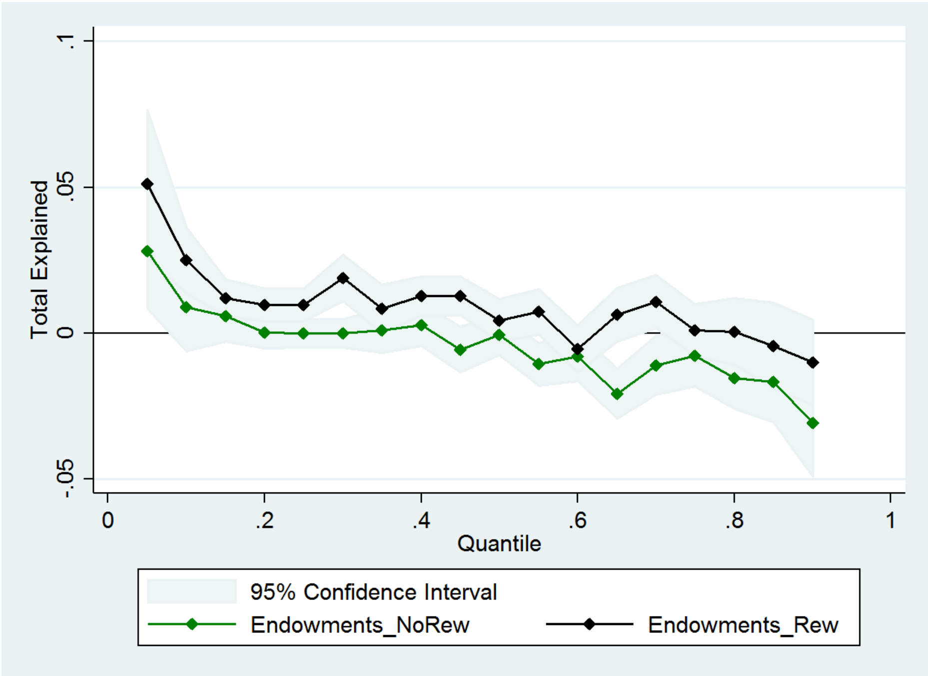

Figure 2: Endowments Effect with and without Reweigthing

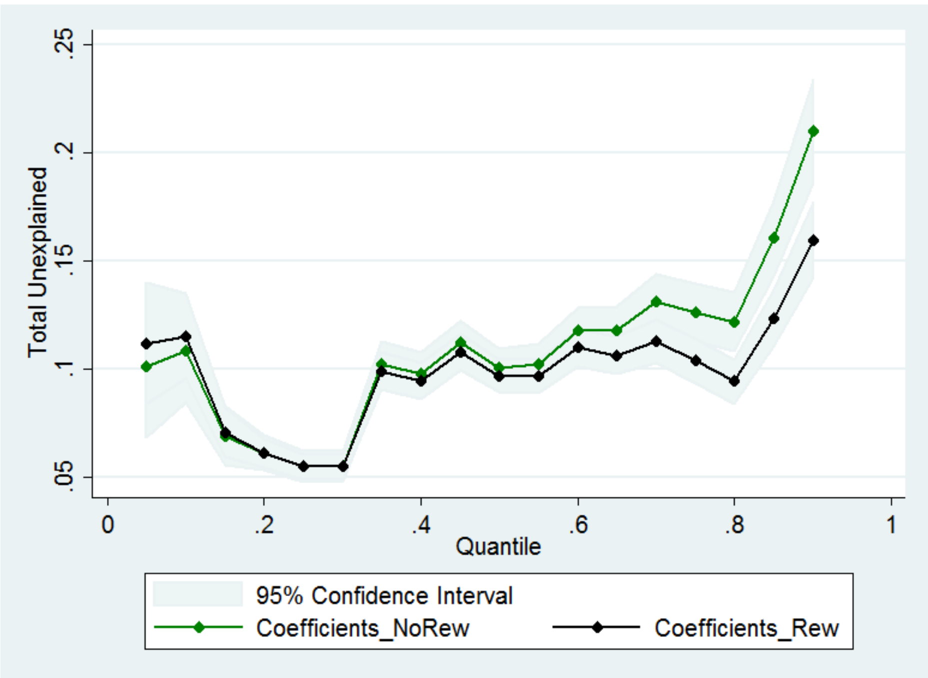

Figure 3: Coefficients Effect with and without Reweighting

4.4 Estimation of the Incidence of Employment

Table 6 shows the estimation outcome from the single-index models (probit, Ichimura and Klein-Spady, respectively). The set of regressors in the selection equations, Z, contains at least one variable not included in X.[32] The following variables are included in the selection equation only: *Age*, *Age5064*, *Partner_Works* as well as *Kids* and *Kids_10*. These regressors are excluded from the wage equation as they should not influence the wage level directly but reservation earnings. The controls for having children, *Kids*, or young children, *Kids_10*, are used to identify the employment decision.[33] The variables are assumed to affect individual propensity to be employed but not the level of (log) hourly wages. The logic behind is that women with children and in particular young children are less likely to accept wage offers due to child-rearing. In the empirical literature, most studies on the relationship between fertility and female labor market participation find a negative correlation among child-care and female labor force participation (Martins, 2001; Mulligan and Rubinstein, 2008; Lee, 2009; Chang, 2011). Contrary to mothers, fathers have higher employment probability. This is due to the persistence of the male-breadwinner and mother-caretaker model in particular in Southern European countries like Italy (Mínguez, 2004). The dummy variable *Age5064* is equal to one if the individual's age is between 50 and 64 years and zero otherwise. Thus, *Age5064* is a proxy for the last career stage. After child-care and -rearing, the employment probability may increase especially for women. The variable *Partner_Works* is equal to one if the spouse or the partner of the individual is employed and zero otherwise. Devereux (2004) and Bar et al. (2015) find a strong relationship between spousal income and individual labor market participation or employment decision. Therefore, omitting a control for the spouse's or partner's labor market status from the selection equation would potentially lead to inconsistent estimates of the wage equation.

The results in Table 6 suggest, on the one hand, that with increasing age, women are more likely to be employed. This may be driven by career breaks due to child-care at earlier career stages. On the other hand, men's incidence of employment decreases slightly with increasing age. Yet, at the final stage of their career both men and women are more likely to accept wage offers. Higher education raises the probability to work for both men and women. Individuals living and working in the North or Centre of Italy have higher probability to be in employment. The positive impact on the probability is highest for employees in Northern Italy. Married women are less likely to be in employment, while married men are more likely to be employed.[34] Holding the Italian citizenship, if significant, has a positive effect on the incidence of employment for female as well as for male employees. Owning a house significantly raises employees' incidence

[32] The set of regressors Z for the employment decision is the same in each binary choice estimation, i.e. in the probit, Ichimura and Klein-Spady model, respectively.

[33] For example Chzhen and Mumford (2011) assume that the age of children in the household does not affect the wage level and use it (inter alia) to identify selection of women in full-time employment in Great Britain.

[34] In the semiparametric models, no significant effect of being married on the employment probability for men is found.

of employment.[35] The control for owning a house includes bank-financed houses. Consequently, individuals paying-off mortgages are more likely to accept a wage offer. For other house owners, the variable *Homeowner*, as a proxy for wealth, controls for wealthier individuals having better networks and hence are more likely to receive job offers. This increases in turn their likelihood to accept a job offer. Having a partner or a spouse in employment significantly increases the employment probability for men in all three models. For women, the effect is negative in the semiparametric models and positive in the probit estimation. Having children reduces as expected the employment probability of women, while it raises the employment probability for men. Having young children is statistically significant and negative for women, while it impacts positively but statistically insignificantly on the probability of accepting a wage offer for men.[36] The coefficient estimates from the semiparametric single-index models, are comparable to each other in terms of magnitude. The coefficient estimates of the probit model are relatively higher compared to the semiparametric binary choice models in absolute terms. Yet, the signs of the coefficient estimates point generally in the same directions in all three models. The difference in magnitude in the point estimates in the probit estimation compared to the outcome from the semiparametric specifications is in line with results obtained by Buchinsky (1998) or Albrecht et al. (2009) and Chzhen and Mumford (2011).

In order to check whether running the computationally cumbersome semiparametric methods is worth it, in Section 4.4.1, the estimation outcome from the semiparametric selection models is compared with the regression outcome from the parametric selection model using a two-point wild-bootstrap test based on the idea in Horowitz and Härdle (1994).

[35] Except for women in the Klein-Spady model, where owning a house has a negative effect on females' employment probability.

[36] In the semiparametric binary choice models, the effect of having young children on the employment probability for men is statistically significant and negative. Yet, the total effect of having children (*Kids* and *Kids_10*) is positive.

Table 6: Estimation Outcome Incidence of Employment

	(1)	(2)	(3)	(4)	(5)	(6)
		Women			Men	
	Probit Employment	Ichimura Employment	Klein-Spady Employment	Probit Employment	Ichimura Employment	Klein-Spady Employment
Constant	-1.335***	-1.335	-1.335	-1.002***	-1.002	-1.002
	(0.092)	(0.092)	(0.092)	(0.109)	(0.109)	(0.109)
Age	0.003**	0.003	0.003	-0.006***	-0.006	-0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age5064	0.598***	0.334***	0.320***	0.259***	0.035**	0.025***
	(0.038)	(0.010)	(0.015)	(0.043)	(0.017)	(0.003)
Elementary_School	-0.070	0.023***	-0.024	-0.354***	-0.021	-0.018***
	(0.059)	(0.009)	(0.023)	(0.063)	(0.026)	(0.006)
High_School	0.410***	0.153***	0.141***	0.189***	0.007	0.001
	(0.023)	(0.002)	(0.007)	(0.022)	(0.005)	(0.002)
University_Degree	0.410***	0.166***	0.208***	0.088***	-0.003	-0.014***
	(0.026)	(0.003)	(0.010)	(0.031)	(0.006)	(0.003)
North	0.961***	0.156***	0.146***	0.888***	0.022***	0.011***
	(0.019)	(0.002)	(0.007)	(0.020)	(0.005)	(0.002)
Centre	0.641***	0.151***	0.100***	0.584***	0.001	0.003
	(0.021)	(0.003)	(0.008)	(0.023)	(0.006)	(0.003)
Married	-0.036	-0.132***	-0.134***	0.489***	-0.004	-0.001
	(0.033)	(0.004)	(0.010)	(0.038)	(0.007)	(0.004)
Italian	0.338***	-0.006	0.107***	0.406***	0.001	0.001
	(0.070)	(0.007)	(0.011)	(0.106)	(0.037)	(0.004)
Homeowner	0.046**	0.010***	-0.031***	0.213***	0.022***	0.007**
	(0.019)	(0.003)	(0.008)	(0.022)	(0.006)	(0.003)
Partner_Works	0.051*	-0.010***	-0.031***	0.167***	0.012*	0.010***
	(0.026)	(0.003)	(0.009)	(0.030)	(0.006)	(0.003)
Kids	-0.220***	-0.164***	-0.096***	0.162***	0.049***	0.018***
	(0.029)	(0.005)	(0.010)	(0.029)	(0.007)	(0.004)
Kids_10	-0.081***	-0.003	-0.037***	-0.012	-0.027***	-0.016***
	(0.027)	(0.004)	(0.010)	(0.039)	(0.006)	(0.004)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,283	30,283	30,283	22,406	22,406	22,406

Bootstrapped standard errors in parentheses, 100 replications

$***p < 0.01, **p < 0.05, *p < 0.1$

Notes: The constant and the *Age* coefficients in the semiparametric binary choice models have been normalized to the corresponding values from the parametric probit model.

4.4.1 Testing for Equality of the Parametric and Semiparametric Binary Choice Model

The results obtained from the different selection models are compared using a modified version of the Horowitz and Härdle (1994) test proposed in Henderson and Parmeter (2015). The test compares the parametric with the semiparametric choice model of the employment decision E on $Z\gamma$. The null hypothesis tests whether the parametric model is the correct specification. In the underlying case, the parametric form is the probit model and hence $H_0 = E(Y|X) = F(Z\gamma)$, where $F(\cdot)$ is the standard normal cumulative distribution function. The alternative hypothesis is $H_1 = E(Y|X) = H(Z\gamma)$, where $H(\cdot)$ is the unknown smooth function. The feasible test statistics looks as follows:

$$T_{HH} = \{E - F(Z\hat{\gamma})\}\{H(Z\hat{\gamma}) - F(Z\hat{\gamma})\} \tag{11}$$

The intuition behind the test is the following: given that $H(\cdot) = F(\cdot)$ holds, the parametric model is specified correctly and, therefore, should not differ from the semiparametric estimate of the function. In this case, cumbersome computation of the semiparametric models is not necessary. Horowitz and Härdle (1994) pre-multiply the right-hand side of equation (11) by a non-negative weighting function that punishes extreme observations. Yet, the test is sensitive to the choice of the weighting function (Proenca, 1993). In the underlying analysis bootstrapping is used what makes the weighting unnecessary (Proenca, 1993; Henderson and Parmeter, 2015). A two-point wild bootstrap in order to calculate the upper-tail bootstrap p-value is used. The p-values in Table 7 reject the parametric model at a 10% significance level in all cases. In comparison with the Ichimura estimation, the probit model is even rejected at a 1% significance level for both men and women.

Table 7: Results of the Horowitz-Härdle Test

	(1)	(2)
	p-Value	
	Female Sample	Male Sample
Probit – Ichimura	0.002	0.002
Probit – Klein and Spady	0.067	0.006

Following Martins (2001), Figure 4 represents the parametric and semiparametric fit for men and women, Figure 5 shows the respective fits for the full sample. The Figures show that the probit specification does not capture the behavior of individuals with low index numbers very well. This is particularly pronounced for women. Hence, the semiparametric models provide more information on the selection behavior of the individuals in the sample.

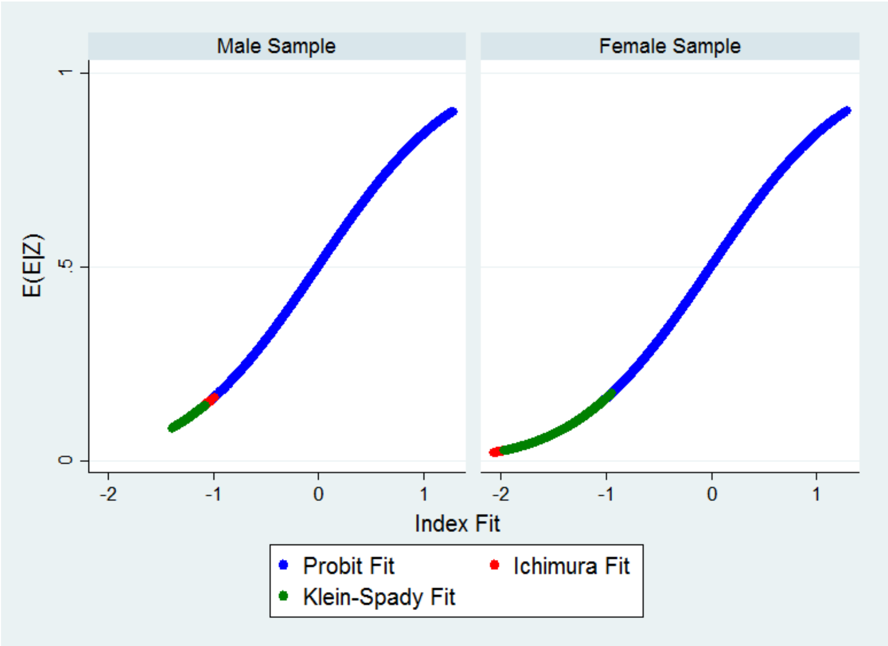

Figure 4: Probit and Semiparametric Fit for the Estimated Index by Gender

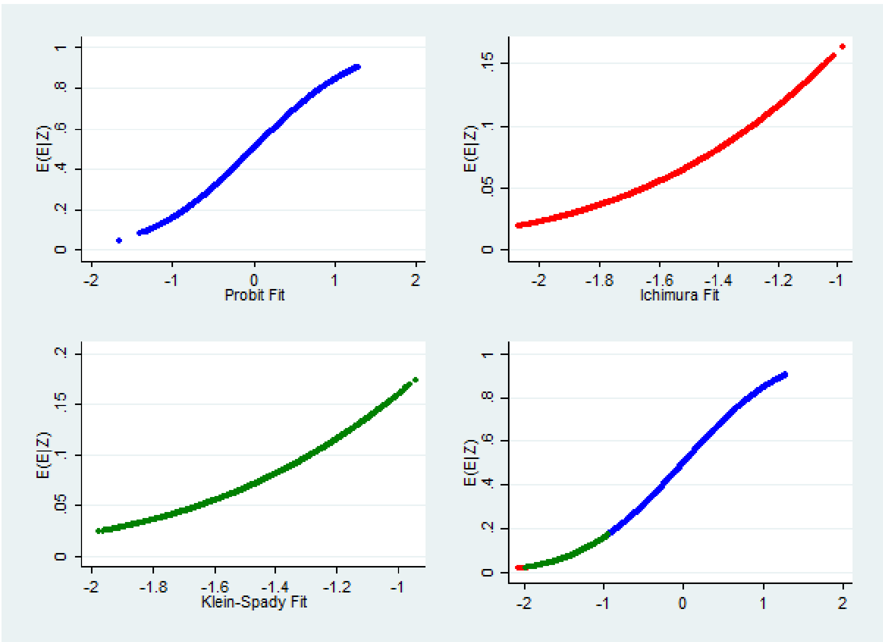

Figure 5: Probit and Semiparametric Fit for the Estimated Index

4.5 RIF-OLS Decomposition along the Wage Distribution with Selection Adjustment

In this Section, we estimate the selectivity-corrected wage model using second-order polynomials.[37] Tables 8–9 show the detailed decomposition outcome at specific quantiles when it is accounted for sample selectivity. Table 10 summarizes the main result; the unexplained component of the GPG being the main driver of the pay disparity at the mean as well as along the wage distribution changes in the case of sample-selection adjustment. The part generally attributed to discrimination is reduced at the bottom but increased at the top of the wage distribution. This implies that without selection correction, we overestimate the part attributed to gender-wage discrimination for low-income earners and underestimate it for high-income earners.

In fact, gender differences in unobservables are main drivers of the GPG at the 10^{th} and 50^{th} percentile. Not accounting for sample selection would therefore significantly underestimate the total explained part at the 10^{th} and 50^{th} percentile. In terms of the coefficients effect, the results suggest that women are paid more from the same set of generally unobservable characteristics at the median and top of the wage distribution. At the bottom, the sign of the selection component in terms of the coefficients effect works in the opposite direction: men gain more than women from the same set of unobservable characteristics. Without selection adjustment, the unexplained component is underestimated at the top but overestimated at the median and bottom. All in all, the selection component is one of the most important components explaining gender differences in pay along the earnings distribution. Hence, otherwise unobservable characteristics and individual heterogeneity contribute significantly to the quantile-specific GPGs. However, the effect differs both in sign and magnitude at the distinct points of the wage distribution.

Table 11 shows that the selection component also significantly contributes to the variation of the GPG across the earnings distribution. Between the top and bottom, differences in the selection correction term increase wage inequality. On the contrary, gender differences in unobservable characteristics reduce wage inequality between the top and median and the median and the bottom of the wage distribution. Different coefficients of unobservables between men and women decreases wage inequality all along the wage distribution. This result is driven by higher prices for women given the same set of unobservable characteristics between men and women at the top of the wage distribution.

In Appendix D, the contribution of the selection component to the GPG at different quantiles as well as across the wage distribution is presented for the model with parametric selection correction.

[37]The polynomials are not orthogonal. However, the selection terms used are not collinear; $Corr(\lambda, \lambda^2) < |0.5|$.

Table 8: RIF-OLS Detailed Decomposition at Different Quantiles with Selection – Ichimura

	(1)	(2)	(3)
	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
GPG (Unadjusted Gap)	0.117***	0.100***	0.179***
	(0.010)	(0.004)	(0.009)
Endowments Effect			
Education	-0.011***	-0.013***	-0.029***
	(0.002)	(0.001)	(0.003)
Experience	0.020***	0.026***	0.068***
	(0.004)	(0.002)	(0.005)
Job Characteristics	0.006	-0.004*	-0.030***
	(0.006)	(0.002)	(0.006)
Occupations and Industries	0.001	-0.000	-0.026***
	(0.004)	(0.002)	(0.006)
Socio-Demographic Background	-0.011***	-0.009***	-0.012***
	(0.002)	(0.001)	(0.002)
Selection	0.050***	0.013***	-0.013
	(0.011)	(0.004)	(0.013)
Total Explained	0.055***	0.012**	-0.042***
	(0.013)	(0.006)	(0.015)
Coefficients Effect			
Education	-0.047*	-0.032***	0.080***
	(0.028)	(0.010)	(0.024)
Experience	-0.010	0.024**	0.142***
	(0.028)	(0.010)	(0.026)
Job Characteristics	-0.011	0.008	0.118**
	(0.052)	(0.020)	(0.048)
Occupations and Industries	-0.290***	0.052**	0.225***
	(0.070)	(0.026)	(0.062)
Socio-Demographic Background	-0.031	-0.038	-0.060
	(0.112)	(0.043)	(0.110)
Selection	0.599	-0.114	-0.971**
	(0.423)	(0.165)	(0.429)
Total Unexplained	0.062***	0.088***	0.221***
	(0.016)	(0.006)	(0.017)

Bootstrapped standard errors in parentheses, 100 replications
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 9: RIF-OLS Detailed Decomposition at Different Quantiles with Selection – Klein-Spady

	(1)	(2)	(3)
	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
GPG (Unadjusted Gap)	0.117***	0.100***	0.179***
	(0.010)	(0.004)	(0.009)
Endowments Effect			
Education	-0.011***	-0.013***	-0.029***
	(0.002)	(0.001)	(0.003)
Experience	0.020***	0.025***	0.065***
	(0.004)	(0.002)	(0.005)
Job Characteristics	0.006	-0.004*	-0.030***
	(0.006)	(0.002)	(0.006)
Occupations and Industries	0.001	-0.000	-0.025***
	(0.004)	(0.002)	(0.006)
Socio-Demographic Background	-0.011***	-0.010***	-0.012***
	(0.002)	(0.001)	(0.002)
Selection	0.079***	0.019**	-0.006
	(0.023)	(0.010)	(0.027)
Total Explained	0.084***	0.018*	-0.037
	(0.023)	(0.010)	(0.026)
Coefficients Effect			
Education	-0.054*	-0.033***	0.079***
	(0.028)	(0.010)	(0.024)
Experience	-0.006	0.022**	0.130***
	(0.028)	(0.011)	(0.026)
Job Characteristics	-0.010	0.009	0.118**
	(0.052)	(0.020)	(0.048)
Occupations and Industries	-0.289***	0.052**	0.225***
	(0.070)	(0.026)	(0.062)
Socio-Demographic Background	-0.045	-0.042	-0.071
	(0.112)	(0.043)	(0.110)
Selection	0.275	-0.040	-0.512
	(0.419)	(0.162)	(0.415)
Total Unexplained	0.033	0.082***	0.216***
	(0.025)	(0.010)	(0.028)
	24,267	24,267	24,267

Bootstrapped standard errors in parentheses, 100 replications

$***p < 0.01, **p < 0.05, *p < 0.1$

Table 10: GPG and Total Unexplained Component with and without Selection

	(1)	(2)	(3)	(4)
	Mean	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
GPG	0.118***	0.117***	0.100***	0.179***
(Unadjusted)	(0.005)	(0.010)	(0.004)	(0.009)
Total Unexplained	0.124***	0.108***	0.100***	0.210***
(No Selection)	(0.007)	(0.012)	(0.005)	(0.012)
Total Unexplained	0.123***			
(Selection – Standard Heckman Two-Stage)	(0.006)			
Total Unexplained		0.105***	0.100***	0.211***
(Selection – Probit)		(0.012)	(0.005)	(0.012)
Total Unexplained		0.062***	0.088***	0.221***
(Selection – Ichimura)		(0.016)	(0.006)	(0.017)
Total Unexplained		0.033	0.082***	0.216***
(Selection – Klein-Spady)		(0.025)	(0.010)	(0.028)

Bootstrapped standard errors in parentheses, 100 replications
$***p < 0.01, **p < 0.05, *p < 0.1$

Notes: For the mean, the difference in the *Total Unexplained* component with no selection and with selection adjustment is statistically significant at a 5% significance level. In the case of the standard probit model, the difference is not statistically significant at all quantiles. For the semiparametric selection models, the difference is statistically significant at a 5% significance level only for the 10^{th} percentile. At the 50^{th} percentile, the difference is statistically significant at a 10% significance level for the component with no selection and the Klein-Spady selection-adjusted component. At the 90^{th} percentile, the difference is not statistically different from zero in both cases. The difference between the respective components has been tested using a two-sample t-test.

Table 11: Gender Wage Inequality – Selection Component

	(1)	(2)	(3)	(4)	(5)	(6)
	90-10		90-50		50-10	
	Ichimura	Klein-Spady	Ichimura	Klein-Spady	Ichimura	Klein-Spady
Unadjusted Change	0.062***		0.079***		-0.018**	
	(0.011)		(0.009)		(0.008)	
Endowments Effect						
Selection	0.072***	0.034***	-0.026*	-0.037***	-0.025	-0.060**
	(0.012)	(0.006)	(0.013)	(0.012)	(0.028)	(0.025)
Coefficients Effect						
Selection	-0.311***	-0.138*	-0.857*	-0.314	-0.472	-0.012
	(0.103)	(0.112)	(0.460)	(0.454)	(0.445)	(0.449)

Bootstrapped standard errors in parentheses, 100 replications
$***p < 0.01, **p < 0.05, *p < 0.1$

5 Conclusion

This paper analyzes the GPG at different points of as well as gender wage inequality across the wage distribution. The empirical application is based on UQR or the RIF-OLS model. This approach allows to decompose the wage equations by gender using a Oaxaca-Blinder type decomposition in detail along the earnings distribution. The method delivers detailed information on the drivers of the pay gap between men and women at specific quantiles. Gender wage inequality in the sample is estimated by the change in the GPGs across the wage distribution, i.e. the 90-10, 90-50 and 50-10 wage gap. The estimation is based on linear RIF regressions, as potential misspecification problems of the RIF-OLS are negligible. The method based on UQRs has several advantages compared to CQR models as for example its intuitive and computationally easy estimation as well as interpretation. However, CQRs are the standard approach in the quantile-regression literature (Fortin et al., 2011). As the work decision may impact differently on men's and women's (log) hourly wages along the earnings distribution, the method is extended in order to allow for sample selection. By adding selection terms as second-order polynomials to the earnings equation, the estimation results are adjusted for potential non-random selection into employment (Buchinsky, 1998). The selection correction focuses on semiparametric models as the selection process may be non-normally distributed (Martins, 2001). Indeed, a two-point wild-bootstrap test, based on Horowitz and Härdle (1994) and comparing the parametric and semiparametric binary choice models, rejects the parametric probit specification.

The analysis in this paper shows that different factors, such as educational attainment, labor market experience and tenure, job characteristics, employment in different industries or demographic and family background characteristics contribute differently to the GPG along the wage distribution. In particular, by splitting the various categories in an endowments and a coefficients part, differences in the contribution to the GPG at different quantiles are found. Individual heterogeneity, like individual ability or personal motivation, and other unobservable labor market characteristics (as for example differences in educational quality) contribute statistically significantly to pay differences between men and women along the wage distribution. Moreover, we detect glass ceiling, i.e. significant differences between the GPG at the top and the bottom or the median of the earnings distribution. In line with this, the wage penalty of being female is highest at the top. The results suggest that it is important to consider GPGs throughout the wage distribution and hence to go beyond the mean. This may be particularly relevant, when it comes to policy implications. Wage structure effects of male-female differences in educational attainment are a main driver of wage inequality between the top and bottom or median quantile, while the endowments effect of gender differences in education significantly lowers wage inequality. Endowments effects of the set of regressors accounting for gender differences in labor market presence across the wage distribution are particularly relevant in contributing to wage inequality as well as a positive GPG at all quantiles. The bottom of the wage distribution is found to be relatively more equal in terms of job characteristics and industrial and occupational differences between men and women in terms of endowments. Differences in demographic and family background characteristics between men and women across the wage distribution both in terms of endowments and coefficients effects are less important. Most of the quantile-specific pay gaps is accounted for by how men and women are rewarded, i.e. by the unexplained component. This finding is in conformity with results obtained in other studies on gender differences in pay for example Blau and Kahn (2016). On the contrary, net differences in endowments, i.e. the total explained part, work towards a reduction of the phenomenon of glass ceiling as well as of the GPGs at the corresponding quantiles. According to which selection adjustment model (parametric or semiparametric) is chosen, the correction terms contribute differently to the quantile-specific GPGs. Yet, in all model specifications, the main pattern of results remains the same. The unexplained part is overestimated at the bottom and median but underestimated at the top of the wage distribution. The extension proposed, to the author's best knowledge, is the first approach allowing to control for selection issues when conducting detailed Oaxaca-Blinder type decompositions based on UQRs along the wage distribution.

References

Albrecht, J., A. Björklund, and S. Vroman (2003): "Is there a Glass Ceiling in Sweden?" *Journal of Labor Economics*, 21, 145–177.

Albrecht, J., A. van Vuuren, and S. Vroman (2009): "Counterfactual Distributions with Sample Selection Adjustments: Econometric Theory and an Application to the Netherlands," *Labour Economics*, 16, 383–396.

Arulampalam, W., A. L. Booth, and M. L. Bryan (2007): "Is there a Glass Ceiling over Europe? Exploring the Gender Pay Gap across the Wage Distribution," *Industrial and Labor Relations Review*, 60, 163–186.

Bar, M., S. Kim, and O. Leukhina (2015): "Gender Wage Gap Accounting: The Role of Selection Bias," *Demography*, 52, 1729–1750.

Blau, F. D. and L. M. Kahn (1992): "The Gender Earnings Gap: Learning from International Comparisons," *American Economic Review*, 82, 533–38.

——— (2003): "Understanding International Differences in the Gender Pay Gap," *Journal of Labor Economics*, 21, 106–144.

——— (2006): "The US Gender Pay Gap in the 1990s: Slowing Convergence," *Industrial Labor Relations Review*, 45–66.

——— (2016): "The Gender Wage Gap: Extent, Trends, and Explanations," Tech. rep., National Bureau of Economic Research.

Blinder, A. (1973): "Wage Discrimination: Reduced Form and Structural Estimates," *Journal of Human Resources*, 8, 436–455.

Borah, B. J. and A. Basu (2013): "Highlighting Differences between Cconditional and Unconditional Quantile Regression Approaches through an Application to Assess Medication Adherence," *Health Economics*, 22, 1052–1070.

Bordogna, L. (2012): "Employment Relations and Union Action in the Italian Public Services-Is There a Case of Distortion of Democracy," *Comparative Labor Law and Policy Journal*, 34, 507.

Brekke, K. and K. Nyborg (2010): "Selfish Bakers, Caring Nurses? A Model of Work Motivation," *Journal of Economic Behaviour and Organization*, 75, 377–394.

Buchinsky, M. (1998): "The Dynamics of Change in the Female Wage Distribution in the USA: A Quantile Regression Approach," *Journal of Applied Econometrics*, 13, 1–30.

Cameron, A. and P. Trivedi (2009): *Microeconometrics: Methods and Application*, Cambridge University Press.

Carneiro, P., J. J. Heckman, and E. J. Vytlacil (2011): "Estimating Marginal Returns to Education," *The American Economic Review*, 101, 2754–2781.

Chzhen, Y. and K. Mumford (2011): "Gender Gaps Across the Earnings Distribution for Full-Time Employees in Britain: Allowing for Sample Selection," *Labour Economics*, 18, 837–844.

Cornelissen, T., C. Dustmann, A. Raute, and U. Schönberg (2016): "From LATE to MTE: Alternative Methods for the Evaluation of Policy Interventions," *Labour Economics*, 41, 47–60.

Devereux, P. J. (2004): "Changes in Relative Wages and Family Labor Supply," *Journal of Human Resources*, 39, 698–722.

DiNardo, J., N. M. Fortin, and T. Lemieux (1996): "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, 64, 1001–44.

Donald, S. G., D. A. Green, and H. J. Paarsch (2000): "Differences in Wage Distributions between Canada and the United States: An Application of a Flexible Estimator of Distribution Functions in the Presence of Covariates," *The Review of Economic Studies*, 67, 609–633.

England, P. (2006): "Towards Gender Equality: Progress and Bottlenecks. In F.D. Blau, M.C. Brinton and D.B. Grusky (Eds.)," *The Declining Significance of Gender?*, 245–265.

Eurostat (2016): "Europe 2020 Employment Indicator," `http://ec.europa.eu/eurostat/documents/2995521/7997105/3-25042017-BP-EN.pdf/377b4834-5a19-42f4-8a2d-36e133ed887d`.

——— (2017): "Gender Pay Gap in Unadjusted Form," `http://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&language=en&pcode=tsdsc340&plugin=1`, (accessed 27-05-2017).

Filer, R. K. (1985): "Male-female Wage Differences: The Importance of Compensating Differentials," *Industrial and Labor Relations Review*, 38, 426–437.

Firpo, S., N. M. Fortin, and T. Lemieux (2009a): "Supplement to 'Unconditional Quantile Regressions' ," *Econometrica Supplemental Material*, 77.

——— (2009b): "Unconditional Quantile Regressions," *Econometrica*, 77, 953–973.

Fortin, N., T. Lemieux, and S. Firpo (2011): *Decomposition Methods in Economics*, Elsevier, vol. 4 of *Handbook of Labor Economics*, chap. 1, 1–102.

Gelbach, J. B. (2016): "When Do Covariates Matter? And Which Ones, and How Much?" *Journal of Labor Economics*, 34, 509–543.

Ghosh, P. K. (2014): "The Contribution of Human Capital Variables to Changes in the Wage Distribution Function," *Labour Economics*, 28, 58–69.

Goldin, C. (2014): "A Grand Gender Convergence: Its Last Chapter," *American Economic Review*, 104, 1091–1119.

Grove, W. A., A. Hussey, and M. Jetter (2011): "The Gender Pay Gap Beyond Human Capital: Heterogeneity in Noncognitive Skills and in Labor Market Tastes," *Journal of Human Resources*, 46, 827–874.

Harrell, F. (2015): *Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis*, Springer.

Heckman, J. (1979): "Sample Selection Bias as a Specification Error," *Econometrica*, 47, 153–61.

Henderson, D. J. and C. F. Parmeter (2015): *Applied Nonparametric Econometrics*, Cambridge University Press.

Hirano, K., G. W. Imbens, and G. Ridder (2003): "Efficient Estimation of Average Treatment Effects using the Estimated Propensity Score," *Econometrica*, 71.

Horowitz, J. L. and W. Härdle (1994): "Testing a Parametric Model Against a Semiparametric Alternative," *Econometric Theory*, 10, 821–848.

Ichimura, H. (1993): "Semiparametric Least Squares (SLS) and Weighted SLS Estimation of Single- Index Models," .

Juhn, C., K. M. Murphy, and B. Pierce (1993): "Wage Inequality and the Rise in Returns to Skill," *Journal of political Economy*, 410–442.

Kahn, L. M. (2015): "Wage Compression and the Gender Pay Gap," *IZA World of Labor*.

Klein, R. W. and R. H. Spady (1993): "An Efficient Semiparametric Estimator for Binary Response Models," *Econometrica*, 387–421.

Longhi, S., C. Nicoletti, and L. Platt (2012): "Explained and Unexplained Wage Gaps across the Main Ethno-Religious Groups in Great Britain," *Oxford Economic Papers*, gps025.

Lucifora, C. and D. Meurs (2006): "The Public Sector Pay Gap In France, Great Britain and Italy," *Review of Income and Wealth*, 52, 43–59.

Machado, J. A. F. and J. Mata (2005): "Counterfactual Decomposition of Changes in Wage Distributions using Quantile Regression," *Journal of Applied Econometrics*, 20, 445–465.

Martins, M. F. O. (2001): "Parametric and Semiparametric Estimation of Sample Selection Models: An Empirical Application to the Female Labour Force in Portugal," *Journal of Applied Econometrics*, 16, 23–39.

Melly, B. (2005a): "Decomposition of Differences in Distribution using Quantile Regression," *Labour Economics*, 12, 577–590.

——— (2005b): "Public-Private Sector Wage Differentials in Germany: Evidence from Quantile Regression," *Empirical Economics*, 30, 505–520.

Mínguez, A. M. (2004): "The Persistence of Male Breadwinner Model in Southern European Countries in a Compared Perspective: Familism, Employment and Family Policies," *Marie Curie Annals*, 4.

Newey, W. K. (2009): "Two-Step Series Estimation of Sample Selection Models," *The Econometrics Journal*, 12.

Oaxaca, R. (1973): "Male-Female Wage Differentials in Urban Labor Markets," *International Economic Review*, 14, 693–709.

Piazzalunga, D. and M. L. Di Tommaso (2015): "The Increase of the Gender Wage Gap in Italy during the 2008-2012 Economic Crisis," .

Pistaferri, L. (1999): "Informal Networks in the Italian Labor Market," *Giornale Degli Economisti e Annali di Economia*, 355–375.

Worldwide-Tax-Summaries (2017): "Italy: Individual – Other Tax Credits and Incentives," http://taxsummaries.pwc.com/ID/Italy-Individual-Other-tax-credits-and-incentives.

Xiu, L. and M. Gunderson (2014): "Glass Ceiling or Sticky Floor? Quantile Regression Decomposition of the Gender Pay Gap in China," *International Journal of Manpower*, 35, 306–326.

A Oaxaca-Blinder Decomposition

The standard approach in decomposing wage differences between groups is the Oaxaca (1973) and Blinder (1973) decomposition approach outlined in the following:

$$\begin{aligned} \bar{Y}_M - \bar{Y}_F &= \bar{X}_M \hat{\beta}_M - \bar{X}_F \hat{\beta}_F \\ &= (\bar{X}_M - \bar{X}_F)\hat{\beta}_M + \bar{X}_F(\hat{\beta}_M - \hat{\beta}_F) \end{aligned} \tag{A.1}$$

where $\bar{Y}_M$ and $\bar{Y}_F$ are the log hourly wages for the male and female sample evaluated at the mean, respectively, with $\bar{X}_G$ being a $1 \times K$ vector of average characteristics and $\hat{\beta}_G$ being a $K \times 1$ vector of estimated coefficients for $G = (F, M)$, with $M = Male$ and $F = Female$. Define $\bar{Y}_M - \bar{Y}_F = \hat{\Delta}$ and $(\bar{X}_M - \bar{X}_F)\hat{\beta}_M = \hat{\Delta}_E$ as well as $\bar{X}_F(\hat{\beta}_M - \hat{\beta}_F) = \hat{\Delta}_C$, with E identifying the *Endowments Effect* and C the *Coefficients Effect*. The endowments effect, $\hat{\Delta}_E$, evaluates the GPG in terms of differences in observable characteristics given male prices. The standard case that is applied here uses male coefficients, $\hat{\beta}_M$, as the non-discriminatory wage structure and hence assumes no discrimination against men. The second term, $\hat{\Delta}_C$, i.e the coefficients part or the adjusted GPG, evaluates the pay gap in terms of different returns for female characteristics.

Table A.1 shows the result from the standard Oaxaca-Blinder decomposition at the mean without and with sample selection correction (column (1) and (2), respectively). For selection correction, the standard Heckman (1979) two-step procedure is applied. The selection component is significant only in terms of the endowments effect and adjusts both the total explained and total unexplained part only slightly. In absolute terms both parts are corrected downwards.

Table A.1: Oaxaca-Blinder Decomposition at the Mean without and with Selection

	(1)	(2)
	No Selection	Selection[a]
GPG (Unadjusted Gap)	0.118***	
	(0.005)	
Endowments Effect		
Education	-0.016***	-0.015***
	(0.001)	(0.001)
Experience_Tenure	0.035***	0.032***
	(0.002)	(0.002)
Job_Char	-0.010***	-0.009***
	(0.003)	(0.003)
Occupations_Industry	-0.007***	-0.007***
	(0.002)	(0.002)
Socio-Demographic_Background	-0.009***	-0.009***
	(0.001)	(0.001)
Selection		0.003**
		(0.001)
Total Explained	-0.007	-0.006
	(0.004)	(0.004)
Coefficients Effect		
Education	0.004	0.005
	(0.011)	(0.013)
Experience_Tenure	0.041***	0.039***
	(0.012)	(0.013)
Job_Char	0.016	0.016
	(0.023)	(0.023)
Occupations_Industry	-0.004	-0.006
	(0.031)	(0.031)
Socio-Demographic_Background	-0.029	-0.032
	(0.052)	(0.053)
Selection		0.010
		(0.040)
Total Unexplained	0.124***	0.123***
	(0.006)	(0.006)

Bootstrapped standard errors in parentheses, 100 replications
$***p < 0.01, **p < 0.05, *p < 0.1$

[a] The selection components are estimated via the classical Heckman two-step correction method (Heckman, 1979).

B Reweighted-Regression Decomposition

If the assumed linearity in the RIF model does not hold, the model is misspecified and the decomposition components are incorrect. Adding a reweighting scheme solves this problem. The reweighted-regression decomposition using the reweighting approach proposed by DiNardo et al. (1996) consists in performing two Oaxaca-Blinder decompositions; one for the endowments and one for the coefficients effect.[38] In order to use men as the non-discriminatory wage structure, the sample of men is reweighted to the sample of women, indicated by the index *rew*. The method uses a semiparametric reweighting factor and creates a counterfactual framework by reweighting men's characteristics to be as women's. The marginal and unconditional wage distribution $Y_M|D_M$ is derived via the law of iterated probabilities by integrating the conditional distribution of wages observed for men given the set of observable characteristics X, $F_{Y_M|X,D_M}$ over the male marginal distribution of X:

$$F_{Y_M|D_M}(Y) = \int F_{Y_M|X,D_M}(Y|X = x)dF_{X|D_M}(x) \tag{B.1}$$

$$\begin{aligned} F_{Y_M^{rew}:X=X|D_F}(Y) &= \int F_{Y_M|X,D_M}(Y|X = x)\Psi(X)dF_{X|D_M}(x) \\ &= \int F_{Y_M|X,D_M}(Y|X = x)dF_{X|D_F}(x) \end{aligned} \tag{B.2}$$

where the dummy variable D_G with $G = M, F$ identifies group membership, for $M = Male$ and $F = Female$ and $\Psi(X)$ is the reweighting factor. It reweights female observations and is derived using the predicted probability of belonging to the male sample, i.e. being male, given X, $Pr(X|D_M = 1)$. The reweighting factor $\Psi(X) = \frac{dF_{X_F}(X)}{dF_{X_M}(X)}$ is the ratio of the marginal distributions of X for women F and men M. As $\Psi(X)$ is simply a function of X, it can be derived using the predicted probability of being a woman given X, $Pr(X|D_F = 1)$, i.e. via standard probit or logit. Since $dF_{X_F}(X) = Pr(X|D_F = 1)$ and $dF_{X_M}(X) = Pr(X|D_F = 0)$, the reweighting factor can be re-written as:

$$\Psi(X) = \frac{Pr(X|D_F = 1)}{Pr(X|D_F = 0)} = \frac{Pr(D_F = 1|X)Pr(D_F = 0)}{Pr(D_F = 0|X)Pr(D_F = 1)} \tag{B.3}$$

In order to obtain $Pr(X|D_F = 1)$, a probit regression for the pooled sample is run. In the probit estimation, all regressors used in the decomposition, as well as a set of interaction terms between educational dummies, experience and occupations (as a proxy for tasks) are included. In particular, for the detailed decomposition, besides the reweighting factor described in equa-

[38] The application of other reweighting procedures is possible. For example, propensity score reweighting could be used (Hirano et al., 2003). Here the method proposed by DiNardo et al. (1996) is used as it relies minimally on functional form assumptions. Alternatively, the model proposed by Ghosh (2014) could be used as the reweigthing may have relatively poor finite sample performance.

tion (B.3), for each covariate k (with $k = 1, 2, \ldots, K$) a reweighting factor using all covariates except X_k is estimated:

$$\Psi_k(X_{K-k}) = \frac{Pr(X_{K-k}|D_F = 1)}{Pr(X_{K-k}|D_F = 0)} = \frac{Pr(D_F = 1|X_{K-k})Pr(D_F = 0)}{Pr(D_F = 0|X_{K-k})Pr(D_F = 1)} \tag{B.4}$$

The counterfactual statistic of each covariate k is obtained by using the product of the reweighting factors (B.3) and (B.4), $\Psi(X)\Psi_k(X_{K-k})$, as weights (instead of using only $\Psi(X)$ as weight). The counterfactual statistic is then subtracted from $\Psi(X)$ yielding the contribution of each covariate k (Fortin et al., 2011). As the effect on the single covariates is estimated conditional on all other covariates, the method is path independent.

In order to obtain a detailed decomposition in the sense of Oaxaca (1973) and Blinder (1973), in a first stage, the distributional changes are estimated separately for an endowments and a coefficients effect. In a second stage, the two effects are further divided into the contribution of each set of covariates (or each covariate) using the RIF-regression model outlined in Section 2.1. The endowments effect is obtained by decomposing the wage gap between the male and the reweighted sample:

$$\begin{aligned} \hat{\Delta}_{E,R} &= \hat{\Delta}_{E,p} + \hat{\Delta}_{E,e} \\ &= \underbrace{(\bar{X}_M - \bar{X}_M^{rew})\hat{\beta}_{M,\tau}}_{\text{Pure Endowments Effect}} + \underbrace{\bar{X}_M^{rew}(\hat{\beta}_{M,\tau} - \hat{\beta}_{M,\tau}^{rew})}_{\text{Specification Error}} \end{aligned} \tag{B.5}$$

where p indicates the *pure effect*, e the part attributed to the *error term* and R the total effect when reweighting is conducted. The index E identifies again the *Endowments Effect*. The specification error in the linear model is equal to zero, if the model is truly linear; $\bar{X}_M^{rew}(\hat{\beta}_{M,\tau} - \hat{\beta}_{M,\tau}^{rew}) = 0$. Differences between the detailed reweighted RIF-decomposition and the RIF decomposition without reweighting are caught by the specification error. These differences can be measured as the difference between the coefficients effect from the model without and with reweigthing (specification error). The additional term in the (total) endowments component, the specification error, allows to draw conclusions on the goodness of specification of the linear model (the specification error is zero if the model is truly linear). Hence, it adjusts the endowments component, when the linear model is not accurately specified. In another Oaxaca-Blinder type decomposition, the coefficients part is calculated. The decomposition is conducted between the reweighted sample, *rew*, and the female sample, F:

$$\begin{aligned} \hat{\Delta}_{C,R} &= \hat{\Delta}_{C,p} + \hat{\Delta}_{C,e} \\ &= \underbrace{\bar{X}_F(\hat{\beta}_{M,\tau}^{rew} - \hat{\beta}_{F,\tau})}_{\text{Pure Coefficients Effect}} + \underbrace{(\bar{X}_M^{rew} - \bar{X}_F)\hat{\beta}_{M,\tau}^{rew}}_{\text{Reweighting Error}} \\ &\approx \bar{X}_F(\hat{\beta}_{M,\tau}^{rew} - \hat{\beta}_{F,\tau}) \end{aligned} \tag{B.6}$$

where the index C identifies the *Coefficients Effect.* The reweighting error, $(\bar{X}_M^{rew} - \bar{X}_F)\hat{\beta}_{M,\tau}^{rew}$, goes to zero given that the following property of large samples holds: $\text{plim}(\bar{X}_F^{rew}) = \text{plim}(\bar{X}_M)$ leading to $\hat{\Delta}_{C,e} \rightarrow 0$ as $N \rightarrow \infty$.[39]

For the quantile-specific reweighted decomposition outcome and the reweighted wage inequality measures shown in Table B.1 and Table B.2, respectively, the pure endowments and coefficients effect are referred to as *Total Explained* or *Total Unexplained.* The application of a reweighting approach may be particularly important when considering RIF regressions as they might not be linear for distributional statistics besides the mean (Fortin et al., 2011). Advantages of the reweighting scheme applied here are the low dependence on functional form assumptions of the (flexible) probit for gender effects and that the procedure yields efficient estimates (Fortin et al., 2011).

[39] Given that the reweighting function has been correctly specified.

Table B.1: RIF-OLS Detailed Decomposition at Different Quantiles with Reweighting

	(1)	(2)	(3)
	10^{th} Percentile F(X) in male sample reweighted to female sample	50^{th} Percentile F(X) in male sample reweighted to female sample	90^{th} Percentile F(X) in male sample reweighted to female sample
GPG (Unadjusted Gap)	0.117***	0.100***	0.179***
	(0.010)	(0.004)	(0.009)
Endowments Effect			
Education	-0.011***	-0.019***	-0.028***
	(0.002)	(0.001)	(0.003)
Experience	0.028***	0.038***	0.062***
	(0.003)	(0.002)	(0.004)
Job Characteristics	0.013***	-0.007***	-0.025***
	(0.004)	(0.002)	(0.005)
Occupations and Industries	-0.002	-0.007***	-0.019***
	(0.004)	(0.002)	(0.005)
Socio-Demographic Background	-0.003***	-0.000	-0.001
	(0.001)	(0.001)	(0.001)
Total Explained	0.025***	0.004	-0.010
	(0.006)	(0.004)	(0.007)
Coefficients Effect			
Education	-0.024	-0.015	0.146***
	(0.028)	(0.011)	(0.025)
Experience	-0.070***	-0.009	0.043*
	(0.027)	(0.010)	(0.024)
Job Characteristics	-0.011	0.005	0.089*
	(0.053)	(0.020)	(0.048)
Occupations and Industries	-0.364***	0.031	0.116*
	(0.073)	(0.028)	(0.064)
Socio-Demographic Background	0.175*	-0.059	-0.212**
	(0.100)	(0.038)	(0.090)
Total Unexplained	0.115***	0.097***	0.160***
	(0.010)	(0.004)	(0.009)
Specification Error	-0.007	0.003	0.05
Reweighting Error	0.016	0.005	0.041

Bootstrapped standard errors in parentheses, 100 replications

$***p < 0.01, **p < 0.05, *p < 0.1$

Notes: The *Total Unexplained* parts from the model without and with reweighting are not statistically significantly different from each other at the 10^{th} and 50^{th} percentile of the wage distribution but statistically significantly different at the 90^{th} percentile. Similarly, the *Total Explained* components with and without reweighting are not statistically significantly different at the bottom and median but statistically significantly different at the top. The difference between the respective parts has been tested using a two-sample t-test.

Table B.2: Gender Wage Inequality – RIF-OLS Decomposition Results with Reweighting

	(1)	(2)	(3)
	90-10 F(X) in male sample reweighted to female sample	90-50 F(X) in male sample reweighted to female sample	50-10 F(X) in male sample reweighted to female sample
Unadjusted Change	0.062***	0.079***	-0.018**
	(0.011)	(0.009)	(0.008)
Detailed Endowments Effect			
Education	-0.017***	-0.009***	-0.008***
	(0.002)	(0.002)	(0.001)
Experience	0.034***	0.024***	0.010***
	(0.002)	(0.003)	(0.002)
Job Characteristics	-0.038***	-0.018***	-0.020***
	(0.003)	(0.001)	(0.002)
Occupations and Industries	-0.017***	-0.012***	-0.006***
	(0.002)	(0.002)	(0.001)
Socio-Demographic Background	0.003	-0.000	0.003
	(0.003)	(0.002)	(0.002)
Total Explained	-0.035***	-0.014***	-0.021***
	(0.005)	(0.004)	(0.003)
Detailed Coefficients Effect			
Education	0.170***	0.161***	0.009
	(0.037)	(0.027)	(0.030)
Experience	0.113***	0.052**	0.061**
	(0.036)	(0.026)	(0.029)
Job Characteristics	0.100	0.084	0.017
	(0.071)	(0.052)	(0.057)
Occupations and Industries	0.480***	0.085	0.396***
	(0.097)	(0.070)	(0.078)
Socio-Demographic Background	-0.387***	-0.154	-0.234**
	(0.135)	(0.098)	(0.107)
Total Unexplained	0.045**	0.063***	-0.018*
	(0.013)	(0.010)	(0.011)
Specification Error	0.057	0.047	0.01
Reweighting Error	0.005	0.016	-0.011

Bootstrapped standard errors in parentheses, 100 replications

$***p < 0.01, **p < 0.05, *p < 0.1$

C Asymptotic Normality of the RIF-OLS Model with Semiparametric Estimators for Selection Correction

We assume that the following model using only the observed data yields biased parameters:

$$RIF(Y;Q_\tau) = X\beta_\tau + u_\tau \tag{C.1}$$

as

$$E[RIF(Y;Q_\tau)|X, E=1] = X\beta_\tau + E[u_\tau|v_\tau > -Z\gamma] \tag{C.2}$$

with $E[u_\tau|v_\tau > -Z\gamma] \neq 0$. Firpo et al. (2009a) derive the asymptotic properties of the RIF-OLS. In the following, the asymptotic normality as derived in Firpo et al. (2009a) is extended for the model with selection correction. Recall that, in the case of semiparametric estimators for selection correction, the RIF-OLS regression model corrected for selection bias at τ has the following form:

$$\begin{aligned}\widehat{RIF}(Y;Q_\tau) &= X\hat{\beta}_\tau + \hat{h}^*_\tau(\hat{m}^*) + \hat{\epsilon}_\tau \\ &= X\hat{\beta}_\tau + \hat{\delta}^*_{1\tau}\lambda^*(Z^*_A\gamma^*)^1 + \hat{\delta}^*_{2\tau}\lambda^*(Z^*_A\gamma^*)^2 + \hat{\epsilon}_\tau \end{aligned} \tag{C.3}$$

where X is a vector of K regressors, $\hat{\epsilon}_\tau$ is the quantile-specific residual.[40] $\hat{\beta}_\tau$ is the corresponding vector of coefficient estimates at τ. $\lambda^*(Z^*_A\gamma^*)$ is the IMR and $\lambda^*(Z^*_A\gamma^*)^2$ is the quadratic term of the IMR, $\hat{\delta}^*_{1\tau}$ and $\hat{\delta}^*_{2\tau}$ are the corresponding coefficient estimates. We assume that the wage model in (C.3) yields consistent and unbiased parameter estimates and hence successfully corrects for sample selection. For each observation i, we have:

$$\widehat{RIF}(Y_i;Q_\tau) = X_i\hat{\beta}_\tau + \hat{\delta}^*_{1\tau}\lambda^*_i(Z^*_A\gamma^*) + \hat{\delta}^*_{2\tau}\lambda^*_i(Z^*_A\gamma^*)^2 + \hat{\epsilon}_{i\tau}$$

where X_i has dimension $1 \times K$ and Y_i is a scalar with sample size $i = 1, \ldots, N$. Following Firpo et al. (2009a), the regression of the RIF-function on X_i, $\lambda^*_i(Z^*_A\gamma^*)$ and $\lambda^*_i(Z^*_A\gamma^*)^2$ yields the following $\hat{\beta}_\tau$ coefficient vector[41]

$$\hat{\beta}_\tau = \frac{\hat{\zeta}(\hat{Q}_\tau)}{f_Y(\hat{Q}_\tau)}$$

with dimension $K \times 1$ and where $f_Y(\hat{Q}_\tau)$ is the kernel density estimator and

$$\hat{\zeta}(\hat{Q}_\tau) = \Omega_X^{-1}\frac{1}{N}\sum_{i=1}^{N}\left\{X_i'\big(\hat{q}_\tau + \mathbb{1}\{Y_i > \hat{Q}_\tau\} - (1-\tau)\big)\right\}$$

[40] For simplicity, $\lambda^*(Z^*_A\gamma^*)^1 = \lambda^*(Z^*_A\gamma^*)$ in the following.

[41] Firpo et al. (2009a) consider the regression of the RIF-function on X_i in the model without selection correction.

with

$$\Omega_X = \frac{1}{N}\sum_{i=1}^{N} X_i' X_i \qquad \text{and} \qquad \hat{q}_\tau = \hat{Q}_\tau f_Y(\hat{Q}_\tau)^{-1}$$

Consequently, as $\hat{\delta}^*_{1\tau}$ and $\hat{\delta}^*_{2\tau}$ are the coefficient estimates obtained from the RIF-OLS regression of $\widehat{RIF}(\cdot)$ on X_i, $\lambda^*_i(Z^*_A\gamma^*)$ and $\lambda^*_i(Z^*_A\gamma^*)^2$, we have:

$$\hat{\delta}^*_{1\tau} = \frac{\hat{\eta}_1(\hat{Q}_\tau)}{f_Y(\hat{Q}_\tau)}$$

$$\hat{\delta}^*_{2\tau} = \frac{\hat{\eta}_2(\hat{Q}_\tau)}{f_Y(\hat{Q}_\tau)}$$

with

$$\hat{\eta}_1(\hat{Q}_\tau) = \Omega^{-1}_{\lambda^*}\frac{1}{N}\sum_{i=1}^{N}\left\{\lambda^*_i(Z^*_A\gamma^*)\big(\hat{q}_\tau + \mathbb{1}\{Y_i > \hat{Q}_\tau\} - (1-\tau)\big)\right\}$$

$$\Omega_{\lambda^*} = \frac{1}{N}\sum_{i=1}^{N}\lambda^*_i(Z^*_A\gamma^*)'\lambda^*_i(Z^*_A\gamma^*)$$

and

$$\hat{\eta}_2(\hat{Q}_\tau) = \Omega^{-1}_{\lambda^{*2}}\frac{1}{N}\sum_{i=1}^{N}\left\{\lambda^*_i(Z^*_A\gamma^*)^2\big(\hat{q}_\tau + \mathbb{1}\{Y_i > \hat{Q}_\tau\} - (1-\tau)\big)\right\}$$

$$\Omega_{\lambda^{*2}} = \frac{1}{N}\sum_{i=1}^{N}\lambda^*_i(Z^*_A\gamma^*)^{2\prime}\lambda^*_i(Z^*_A\gamma^*)^2$$

Then, we have:

$$\sqrt{Nh}(\hat{\tilde{\beta}}_\tau - \tilde{\beta}_\tau) \xrightarrow{D} N(0, V_{OLS})$$

with

$$\hat{\tilde{\beta}}_\tau = \begin{pmatrix}\hat{\beta}_\tau \\ \hat{\delta}_{1\tau} \\ \hat{\delta}_{2\tau}\end{pmatrix} \qquad \text{and} \qquad \tilde{X} = \Big(X, \lambda^*(Z^*_A\gamma^*), \lambda^*(Z^*_A\gamma^*)^2\Big)$$

having dimension $K+1+1 \times 1$, where $K+1+1 = K^*$ and $V_{OLS} = V_{OLS}(Q_\tau, \kappa)$ with $\kappa(\cdot)$ being a real-value kernel function and positive bandwidth h. Following Firpo et al. (2009a), the asymptotic variance can then be represented as:

$$V_{OLS}(Q_\tau,\kappa)=\lim_{h\downarrow 0}\left\{\frac{1}{f_y^2(Q_\tau)}\tilde{\beta}_\tau\tilde{\beta}_\tau' E[(f_y(Q_\tau))^2]+\right.$$
$$\left.=+\frac{1}{f_y^2(Q_\tau)}Var[\sqrt{h}\tilde{\Omega}_{\tilde{X}}^{-1}\tilde{X}u(Q_\tau)+\tilde{\beta}_\tau(q_\tau+\mathbb{1}\{Y>Q_\tau\}-(1-\tau))]\right\}$$

where

$$\tilde{\Omega}_{\tilde{X}}=\frac{1}{N}\sum_{i=1}^{N}\tilde{X}_i'\tilde{X}_i$$

$$u(Q_\tau)=q_\tau+\mathbb{1}\{Y>Q_\tau\}-(1-\tau))-\tilde{X}_i\tilde{\zeta}(Q_\tau)$$

and

$$\tilde{\zeta}(Q_\tau)=\begin{pmatrix}\zeta_\tau(Q_\tau)\\ \eta_{1\tau}(Q_\tau)\\ \eta_{2\tau}(Q_\tau)\end{pmatrix}$$

The kernel density estimator, $\hat{f}_y(\hat{Q}_\tau)$, has an asymptotic squared bias that will go faster to zero than the variance (Firpo et al., 2009a). A possible estimator of $V_{OLS}(Q_\tau,\kappa)$ is $\hat{V}_{OLS}(\hat{Q}_\tau,h\kappa)$ (see Firpo et al., 2009a). Assuming that $E[u(Q_\tau)|\tilde{X}]=0$ and $\tilde{\beta}_\tau=\text{UQPE}_\tau$, then:

$$\text{plim}_{h\downarrow 0}\,\hat{V}_{OLS}(\hat{Q}_\tau,h,\kappa)=V_{OLS}(Q_\tau,\kappa)$$

D The RIF-OLS Model with Parametric Estimators for Selection Correction

If the selection process is assumed to be normally distributed, the probit model can be used for selection adjustment. Following Heckman (1979), the RIF-OLS model corrected for sample selection using a parametric estimator for sample correction is:

$$\widehat{RIF}(Y; Q_\tau) = X\hat{\beta}_\tau + \hat{\delta}_\tau \lambda(Z_A \hat{\gamma}) + \hat{\epsilon}_\tau \tag{D.1}$$

where $\lambda(Z_A\hat{\gamma})$ is the standard IMR evaluated at $Z_A\hat{\gamma}$, $\hat{\delta}_\tau$ is the corresponding coefficient estimate and $\hat{\epsilon}_\tau$ is the quantile-specific residual. Asymptotic normality of the RIF-OLS model corrected for sample selection using a parametric estimator follows from the proof provided by Heckman (1979) for the parametric Heckman estimator at the mean.

The components of the quantile-specific GPG adjusted for selection with the parametric selection correction term are provided in Table D.1. The effect of the estimated selection part due to differences in endowments is less strong compared to the results obtained in Section 4.5 but points generally in the same direction; positive at the bottom, negative at the top of the earnings distribution. At the median no effect is found in the model with parametric selection correction. Differences in the selection effect in terms of the unexplained part have again smaller point estimates but the same sign. Except for the median, where the selection effect is slightly negative in the parametric selection correction approach. Table D.2 shows that gender differences in unobservables (given same prices) do not differ significantly across the wage distribution when the parametric correction approach is applied. Similarly, differences in prices between men and women to the same set of unobservables from higher to lower quantiles do not significantly impact on the variation of the GPG across the distribution.

Table D.1: RIF-OLS Detailed Decomposition at Different Quantiles with Selection – Probit

	(1)	(2)	(3)
	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
GPG (Unadjusted Gap)	0.117***	0.100***	0.179***
	(0.010)	(0.004)	(0.009)
Endowments Effect			
Education	-0.010***	-0.013***	-0.029***
	(0.002)	(0.001)	(0.003)
Experience	0.018***	0.025***	0.067***
	(0.004)	(0.002)	(0.005)
Job Characteristics	0.006	-0.004*	-0.030***
	(0.006)	(0.002)	(0.006)
Occupations and Industries	0.001	-0.001	-0.025***
	(0.004)	(0.002)	(0.006)
Socio-Demographic Background	-0.005**	-0.009***	-0.014***
	(0.002)	(0.001)	(0.003)
Selection	0.004**	0.000	-0.001
	(0.001)	(0.001)	(0.002)
Total Explained	0.012	-0.000	-0.032***
	(0.008)	(0.004)	(0.009)
Coefficients Effect			
Education	-0.024	-0.026**	0.092***
	(0.029)	(0.011)	(0.026)
Experience	0.012	0.025**	0.121***
	(0.027)	(0.010)	(0.025)
Job Characteristics	-0.011	0.008	0.116**
	(0.052)	(0.020)	(0.048)
Occupations and Industries	-0.293***	0.051**	0.225***
	(0.070)	(0.026)	(0.062)
Socio-Demographic Background	0.082	-0.025	-0.116
	(0.135)	(0.052)	(0.130)
Selection	0.110	0.006	-0.064
	(0.080)	(0.030)	(0.071)
Total Unexplained	0.105***	0.100***	0.211***
	(0.012)	(0.005)	(0.012)

Bootstrapped standard errors in parentheses, 100 replications
$***p < 0.01, **p < 0.05, *p < 0.1$

Table D.2: Gender Wage Inequality – Selection Component using Parametric Selection Correction

	(1)	(2)	(3)
	90-10	90-50	50-10
		Probit	
Unadjusted Change	0.062***	0.079***	-0.018**
	(0.011)	(0.009)	(0.008)
Endowments Effect			
Selection	-0.005	-0.001	-0.004
	(0.008)	(0.002)	(0.002)
Coefficients Effect			
Selection	0.174	-0.070	-0.104
	(0.107)	(0.077)	(0.088)

Bootstrapped standard errors in parentheses, 100 replications
$***p < 0.01, **p < 0.05, *p < 0.1$

E Definition of Variables

Table E.1: Definition of Variables

Variable Name	Definition
	Dependent Variables
Lhwage	The natural logarithm of net hourly wages; hourly wages in Euros, net of taxes and social security contributions
E (Employment)	One if the respective individual is in employment, zero otherwise
	Independent Variables
	Dummy and Interaction Effects
female	One if the respective individual is a woman, zero otherwise
Education $\times$ Experience	Quadratic interactions between educational dummies (*Elementary_School*, *High_School*, *University_Degree*) and experience (*Exper*)
Education $\times$ Occupation	Quadratic interactions between educational dummies (*Elementary_School*, *High_School*, *University_Degree*) and occupational dummies (Manager, Intermediate_Prof)
Experience $\times$ Occupation	Quadratic interactions between experience (*Exper*) and occupational dummies (*Manager*, *Intermediate_Prof*)
	Education
Elementary_School	One if the highest educational attainment of the individual is *Elementary_School*, zero otherwise
High_School	One if the highest educational attainment of the individual is *High_School*, zero otherwise; *High_School* corresponds to 13 years of schooling
University_Degree	One if the highest educational attainment of the individual is *University_Degree*, zero otherwise
Max_D_Mark	One if the best degree mark was attained (conditional on having a *University_Degree*), i.e. *110 e lode*, zero otherwise
	Experience
Exper	Number of years of prior work experience of the individual
Exper2	*Exper* squared
Tenure	Number of years the individual has worked for his or her current employer
	Job Characteristics
Work_Climate	Individual's level of satisfaction with the working climate at the individual's current job $\in (0, 4)$ where 4 is the highest level of satisfaction and 0 the lowest
Work_Stab	Individual's level of satisfaction with the stability of the individual's

	current job $\in (0, 4)$, where 4 is the highest level of satisfaction and 0 the lowest
Work_Time	Individual's level of satisfaction with the working time at the individual's current job $\in (0, 4)$, where 4 is the highest level of satisfaction and 0 the lowest
Work_Task	Individual's level of satisfaction with the tasks at the individual's current job $\in (0, 4)$, where 4 is the highest level of satisfaction and 0 the lowest
Part	One if the individual holds a part-time contract, zero otherwise
Contract_Type	One if the individual holds an unlimited contract, zero otherwise

Occupations and Industries

Manager	Intellectual professions; scientific, and highly specialized occupations
Intermediate_Prof	Intermediary positions in commercial, technical or administrative sectors, health services and technicians
Sec_02 - Sec_15	Sectoral dummies for employment in the following sectors or industries: manufacturing, energy, construction, tourism, commerce, transport, communication, financial activities, service industry, public administration, education, health, sciences and family services, respectively

Socio-Demographic Background

Age	Age of the individual (in years) $\in (18, 64)$
Age5064	One if the age of the individual is between fifty and sixty-four years, 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
Homeowner	One if the individual owns a house (including houses financed by bank loans), zero otherwise
Partner_Works	One if the partner or the spouse of the individual is employed, zero otherwise
Married	One if the individual is married, zero otherwise
Italian	One if the individual is Italian, zero otherwise
Educ_Moth_Uni	One if the mother of the individual holds a university degree, zero otherwise
Educ_Fath_Uni	One if the father of the individual holds a university degree, zero otherwise
Kids	One if the individual has at least one child, zero otherwise
Kids_10	One if the age of the youngest child of the individual is less than ten years, zero otherwise
Year_1-Year_5	Year dummies, one if year = 2005, 2006, 2008, 2010, 2011, respectively, and zero otherwise

Selection

λ	Measures the selection bias from the employment decision

F Regression Output OLS, UQR and CQR

Table F.1: OLS, UQR and CQR of Log Hourly Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		10^{th} Percentile		50^{th} Percentile		90^{th} Percentile	
	OLS	UQR	CQR	UQR	CQR	UQR	CQR
female	-0.122***	-0.115***	-0.117***	-0.106***	-0.112***	-0.181***	-0.150***
	(0.005)	(0.012)	(0.007)	(0.005)	(0.004)	(0.012)	(0.009)
Elementary_School	-0.073***	-0.009	-0.040*	-0.065***	-0.080***	-0.108***	-0.042
	(0.019)	(0.044)	(0.023)	(0.016)	(0.014)	(0.031)	(0.036)
High_School	0.109***	0.084***	0.095***	0.067***	0.091***	0.205***	0.126***
	(0.006)	(0.016)	(0.009)	(0.005)	(0.004)	(0.012)	(0.009)
University_Degree	0.202***	0.193***	0.163***	0.170***	0.193***	0.312***	0.258***
	(0.009)	(0.021)	(0.016)	(0.009)	(0.007)	(0.021)	(0.013)
Max_D_Mark	0.032*	0.054**	0.086***	0.042***	0.025**	0.013	0.008
	(0.016)	(0.026)	(0.026)	(0.012)	(0.011)	(0.035)	(0.028)
Exper	0.015***	0.029***	0.019***	0.011***	0.014***	0.013***	0.011***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Exper2	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.005***	0.002***	0.004***	0.004***	0.005***	0.010***	0.004***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Work_Climate	-0.003	0.010	-0.002	-0.000	-0.001	-0.005	-0.002
	(0.003)	(0.006)	(0.004)	(0.002)	(0.002)	(0.007)	(0.005)
Work_Stab	0.015***	0.021***	0.032***	0.008***	0.008***	0.006	0.003
	(0.003)	(0.005)	(0.004)	(0.002)	(0.002)	(0.006)	(0.004)
Work_Time	0.013***	0.004	0.005	0.010***	0.013***	0.022***	0.011***
	(0.003)	(0.006)	(0.005)	(0.002)	(0.002)	(0.005)	(0.004)
Work_Task	0.010***	0.001	-0.001	0.010***	0.009***	0.021***	0.023***
	(0.003)	(0.007)	(0.005)	(0.003)	(0.003)	(0.007)	(0.007)
Part	0.036***	-0.046**	-0.040***	0.041***	0.043***	0.056***	0.098***
	(0.008)	(0.021)	(0.015)	(0.007)	(0.006)	(0.015)	(0.013)
Contract_Type	0.075***	0.204***	0.180***	0.050***	0.040***	-0.017	0.017
	(0.007)	(0.020)	(0.017)	(0.005)	(0.005)	(0.011)	(0.011)
Intermed_Prof	0.055***	0.086***	0.062***	0.052***	0.058***	0.067***	0.047***
	(0.005)	(0.013)	(0.008)	(0.005)	(0.004)	(0.013)	(0.009)
Manager	0.116***	0.034*	0.039**	0.083***	0.120***	0.303***	0.188***
	(0.010)	(0.018)	(0.018)	(0.007)	(0.007)	(0.025)	(0.016)
North	0.056***	0.177***	0.103***	0.026***	0.038***	0.034***	0.032***
	(0.006)	(0.015)	(0.010)	(0.005)	(0.005)	(0.010)	(0.009)
Centre	0.025***	0.132***	0.071***	-0.007	0.013**	-0.005	0.004
	(0.007)	(0.017)	(0.011)	(0.005)	(0.006)	(0.013)	(0.009)
Italian	-0.001	0.086	0.002	-0.005	-0.020	-0.080*	-0.067
	(0.023)	(0.055)	(0.042)	(0.019)	(0.017)	(0.044)	(0.046)

Married	0.067***	0.029***	0.053***	0.065***	0.056***	0.092***	0.074***
	(0.005)	(0.009)	(0.007)	(0.005)	(0.005)	(0.014)	(0.010)
Homeowner	0.029***	0.076***	0.024***	0.024***	0.025***	0.031***	0.043***
	(0.006)	(0.015)	(0.009)	(0.005)	(0.005)	(0.012)	(0.008)
Educ_Fath_Uni	0.026**	-0.026	-0.021	0.021**	0.033***	0.073***	0.039**
	(0.013)	(0.020)	(0.024)	(0.009)	(0.011)	(0.027)	(0.018)
Educ_Moth_Uni	0.005	0.042	0.018	0.014	0.002	-0.018	0.026
	(0.015)	(0.032)	(0.026)	(0.011)	(0.008)	(0.028)	(0.021)
Constant	1.418***	0.616***	0.959***	1.589***	1.500***	1.825***	1.861***
	(0.032)	(0.082)	(0.053)	(0.023)	(0.025)	(0.066)	(0.061)
Sectoral Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses for OLS

Bootstrapped standard errors in parentheses, 100 replications, for UQR and CQR

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