# An Econometric Analysis of the Gender Pay Gap in Italy among Young Adults.

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**Abstract**
The aim of this paper is to carry out an econometric analysis of the gender pay gap among young adults in Italy. Specifically I aim to test the statistical significance of the gender pay gap and to decompose it into two terms: one concerning differences on individual characteristics, the other one regarding difference on returns of the individual characteristics. To this end, I estimate three econometric models: Blinder-Oaxaca model standard, Blinder-Oaxaca model adjusted for the Heckman method, and the Machado-Mata model. According to the results, the gender pay gap is statistically significant and it has a U-shaped pattern along the quantile distribution. There are the effects of *sticky floor* and *glass ceiling*, with the prevalence of the former. According to the results, gender pay gap depends mainly on the difference on individual returns, and this might indicates the presence of gender discrimination.

**JEL code:** J24, J31, J71.

**Keyword:** gender pay gap, Mincerian equation, Blinder-Oaxaca decomposition, selection effect, Machado-Mata decomposition.

## 1.INTRODUCTION

The socioeconomic conditions of Italian young adults is very difficult (Checchi, D. and Peragine V., 2010). In labour market terms, they have low probability to find a job with a good wage and contract due to the "flex-insecurity". In financial terms, they are excluded of credit market, because they have precarious economic conditions. In social terms, although they have high levels of human capital, they do not represent the engine of the Italian economic growth. Finally in political terms, institutions do not appropriately represent their voice. Then, for all these reasons there is in Italy an intergenerational inequality. Another inequality characterises negatively Italy: it is the gender inequality. Females have less socioeconomic opportunities than males. Within international rankings, Italy has a position too low respect to its rank in economic classification (UNDP 20011). Other studies have analysed the gender pay gap in Italy, with respect to total population such as Centra and Cutillo (2009), and Addabbo and Favaro (2007). Instead, in this paper I intend to focus on gender inequality inside the young adult class in order to check if young adult females represent the weakest social group. Thus, the proposal of this paper is to analyse the gender pay gap among young adults aged between 25 and 45 years in Italy by an econometric study. Specifically, I aim to test the statistical significance of the gender pay gap and to decompose it into two terms: one concerning differences on individual characteristics, the other one regarding differences on returns of individual characteristics. The first model concerns the standard Blinder-Oaxaca decomposition (1973). Initially, I estimate Mincerian wage equations, where the logarithm of wages is a function of a set of individual characteristics, both for total population and separately for males and females. Secondly, I decompose the gender pay gap estimated previously, in three parts regarding: differences in individual characteristics called *characteristics* effect, the difference in returns of individual characteristics called *returns* effect, and the *interaction* effect, that is a combination of both. The second model concerns the Blinder-Oaxaca decomposition with Heckman's method (1979). In this model, I consider the process of non-random selection of women within labour market. Initially, I estimate employment equation (with a probit model) and then I calculate the Mincerian equation of women, where the selection effect is the coefficient of the inverse Mill's ratio obtained from the previous equation. Finally, I apply the decomposition of the gender pay gap with the same components of the first model, but in this case adjusted for non-random selection. The third model concerns the Machado Mata's decomposition (2005). In this case, the gender pay gap is decomposed by using quantile regressions. Firstly I estimate three quantile Mincerian equations and after I decompose the gender pay gap into two parts: *characteristics* effect and *returns* effect. In this way, I am able to capture the trend of two effects along the wage quantile distribution.

According to the results, gender pay gap is statistically significant and it depends mainly on different returns of individual characteristics. This outcome might indicate the presence of processes of gender discrimination among young adults.

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## 2. THE VARIABLES ANALYSED

With reference to database, data derive from 2010 Computer Assisted Telephone Interview (CATI) Survey of Department of Statistical Sciences, Sapienza University of Rome[2]. As in all CATI analyses, there can be the measurement error due to the errors of imputation by the interviewers, but I assume that such type of errors is random.

Let us describe the variables considered in all models estimated. Firstly, observations are 344 (154 males and 190 females). In analysis, I use the method of weighted analytic weights, according to which the weights are inversely proportional to the variance of observations. Dependent variable is the logarithm of monthly wages. Maximum and minimum values of monthly wage are respectively 2,500 euro and 208 euro for women, and 4,000 euro and 100 euro for men. While the mean values for women and men are respectively about 1,127 and 1,455 euro. This variable is "sensitive": in fact general survey includes about 1,300 individuals, but only 344 have communicated their average net monthly wage, confirming that this variable is actually "sensitive". Furthermore, data on wage are quite subjective, in the sense that individuals can overestimate or underestimate the actual amount of wage received for various subjective reasons.

Independent variables are the following age, human capital, full-time, job position. The variable *age* has the range between 25 and 45 years, with mean equal 36.5 years. The variable *human capital* is takes value 1 for "Primary school", 2 for "Secondary school/Junior high", 3 for "Professional Certification", 4 for "Secondary school/ high", 5 for "First cycle-Bachelor", 6 for "Second cycle degree" or "Single cycle degree", or "Master" or "PHD degree". The variable *fulltime* takes value 0 for part-time and 1 for full-time: males have an higher frequency of full-time contracts. Finally, the variable *job position* takes value 1 for "Worker", 2 for "Servant", 3 for "Executive", 4 for "Manager" (see Tables A1, A2, A3 in appendix).

Let us underline for each variable gender differences among variables (see Tables B1, B2, B3, B4 in appendix). With regard to *age*, for a better summary we consider four age groups: 25-29 years, 30-34 years, 35-39 years, 40-45 years. For each class, the percentage of males is about 28, 22, 21 and 29 percent, while the percentage of females is 6, 14, 37 and 43 percent. So in both genders, the relative majority is concentrated in the last class of individuals (40-45 years). With reference to variable *human capital*, for both genders the relative majority of individuals attended high secondary school (corresponding to the value 4), respectively the 60 percentage of males and the 53 per cent of females. In the highest human capital level (corresponding to the value 6), the percentage of females is greater than that of males by about 10 percentage points (25 per cent and 15 per cent). With reference to the dummy variable *fulltime*, women have the highest percentage of part-time (33 percent females and 11 percent males respectively). The female work participation is less than male due to family division of labour, according to which women have to do care and household activities. Finally, as regards the variable *job position*, for both sexes, the two-third of individuals are "servant". Males have a higher percentage of workers (equal to 29 percent, while the percentage for females is 16). For the other positions there are no significant differences.

## 3. THE BLINDER-OAXACA STANDARD MODEL

The first method refers to the model built by Blinder (1973) and Oaxaca (1973). In the first step, I estimate three wage equations regarding respectively total population, males and females. The wage equation used is a Mincerian equation where the wage depends on individual characteristics. In formal terms, the function is the following:

$$Y_{ij} = X'_{ij}\beta + \varepsilon_{ij}$$

where $Y_{ij}$ is the vector of logarithms of monthly wage, *i* indicates the individual, *j* denotes the group of reference (males, females and total), $X_{ij}$ indicates the vector of individual explanatory variables previously described: *age*, *human capital*, *fulltime*, *job position*. Finally, $\varepsilon_{ij}$ is the residual term normally distributed. In the estimation of the total population, there is also the dummy variable *female*, which takes the value 1 if the individual is a woman. The estimated model is the Ordinary Least Squares (OLS). The results show that being a woman is a penalizing factor for earning, while wage grows with age, human capital, job position, and the possession of full-time contract impacts positively on wage levels. For both genders, the impacts of these positive factors are similar. The variable *full-time* is the most influent, followed by *job position*, *human capital* and *age*. (see Tables C1, C2, C3, C4 in appendix)

In the second step, I estimate the gender pay gap by using the previous equations. Primarily, I define the gender pay gap *G* as follows

$$G = E(Y_{iM}) - E(Y_{iF}) = E(X_{iM})'\beta_M - E(X_{iF})'\beta_F$$

where $E(Y_{iM})$ and $E(Y_{iF})$ are the expected values of wages for males and females.

[2] The CATI survey has been performed within the research project "Risk and Safety: precarious work, strategies and courses of life insurance. Research on forms of economic protection, insurance and welfare of young Italians" directed by Giovanni Battista Sgritta, coordinated by Fiorenza Deriu (Sapienza University of Rome).

The decomposition of variable *G* is the following

$$G = [E(X_{iM} - X_{iF})]' \beta_F + E(X_{iF})(\beta_M - \beta_F) + [E(X_{iM} - X_{iF})]'(\beta_M - \beta_F).$$

In this way, the gender pay gap is composed of three terms $G = C + R + I$

The first term $C = [E(X_{iM} - X_{iF})]' \beta_F$ indicates the *characteristics effect*: it evaluates the gender pay gap in terms of characteristics at the rate of return of the characteristics of females. The second term $R = E(X_{iF})(\beta_M - \beta_F)$ concerns the *returns effect*: it evaluates the gender pay gap in terms of different returns at the levels of female characteristics. This term can represent the discrimination suffered by women. Finally, third term $I = [E(X_{iM} - X_{iF})]'(\beta_M - \beta_F)$ concerns the *interaction effect*: it is a combination of previous effects.

According to the results, women have lower wages. The gender pay gap is statistically significant and it is about 23 percent. The average wage of males is about 1,372 euro while that one of females is about 1,052 euro. The *characteristics effect* is no significant at general level, but it is significant for specific characteristics. With reference to the *full-time* dummy it is significant and positive at 1 per cent. With reference to the *age*, it is significant and negative at 10 percent. With reference to the *human capital*, it is significant at 10 percent and negative, indicating that women are more qualified then men. The *returns effect* is positive and significant at 1 percent and it is primarily linked with *full-time* dummy (significant at 5 percent). This fact means that the gender pay gap mainly concerns individuals with full-time contract. The returns effect is about 69 percent. Finally, the *interaction effect* is positive and significant at 5 percent.

**Table 1. Blinder Oaxaca decomposition: OLS model**

| | | | | |
|---|---|---|---|---|
| n. of observations tot. | 344 | | | |
| n. of observations males | 154 | | | |
| n. of observations females | 190 | | | |
| **dip. variable = wage** | **Coef.** | **Std. Err.** | **z** | **P>\|z\|** |
| males | 7.224 | 0.030 | 240.570 | 0.000 |
| females | 6.958 | 0.029 | 241.650 | 0.000 |
| difference (M-F) | 0.266 | 0.042 | 6.390 | 0.000 |
| characterstics effect | 0.030 | 0.030 | 1.010 | 0.311 |
| returns effect | 0.183 | 0.039 | 4.730 | 0.000 |
| interaction effect | 0.052 | 0.027 | 1.940 | 0.053 |
| | *characteristics effect* | | | |
| age | -0.021 | 0.011 | -1.880 | 0.060 |
| human capital | -0.021 | 0.013 | -1.650 | 0.098 |
| fulltime | 0.084 | 0.019 | 4.500 | 0.000 |
| job position | -0.012 | 0.010 | -1.170 | 0.241 |
| | *returns effect* | | | |
| age | 0.103 | 0.228 | 0.450 | 0.650 |
| human capital | -0.157 | 0.130 | -1.200 | 0.229 |
| fulltime | 0.136 | 0.066 | 2.050 | 0.040 |
| job position | -0.081 | 0.112 | -0.720 | 0.472 |
| constant | 0.182 | 0.270 | 0.670 | 0.501 |
| | *interaction effect* | | | |
| age | -0.004 | 0.009 | -0.450 | 0.656 |
| human capital | 0.008 | 0.009 | 0.990 | 0.321 |
| fulltime | 0.044 | 0.023 | 1.930 | 0.053 |
| job position | 0.004 | 0.006 | 0.620 | 0.532 |

M: males; F: females; Coef.: coefficients; Std. Err.: standard error; z: critical value; P>z: p-value; [95% Conf. Interval]: interval of confidence.

## 4. THE BLINDER-OAXACA MODEL WITH SELECTION

The previous model can be extended by considering the process of non-random selection of women employed. In fact, the selection process can depend on unobservable factors. This problem can make regressions incorrect and inconsistent. In order to adjust the decomposition, I follow the Heckman's method (1979) (see also Powell 1994) according to which in the first step I estimate the process of female employment obtaining the correction term called lambda or reverse Mill's ratio. Successively, I introduce this term in the decomposition of gender pay gap.

I estimate the female employment equation by the following probit model

$$\Pr ob(q_{iF} = 1) = \frac{1}{\exp(Z'_{iF}\,\gamma_F)} + \nu_{iF}$$

where *q* is the dummy variable *employee*, and $Z_i$ is the vector of independent variables that are: the dummy variable *children* (it is equal to 1 if the woman has one or more children, while it is equal to zero in the other cases), *human capital* and the dummy *north* (it is equal to 1 if individual lives in the North of Italy), (see Tables D1, D2, D3 in appendix). According to data, the 63 percent of women is employed, while the 80 percent of women have one or more children. According to the results, (see Table D4 in appendix) having an high level of human capital and living in the North of Italy increase the probability of being employed. Especially the latter factor is significantly the most relevant. This confirms the Italian territorial gap according to which the North continues to be the area with the greatest economic development and with the highest employment rates.

Finally, the motherhood reduces the chances of being employee: in fact, the variable *children* has a significant and negative coefficient. Two could be the causes of this outcome in the labour market. With reference to the labour supply, motherhood tends to delay the decision to seek a job (Battistoni 2005; Corsi et al. 2007). With the reference to labour demand, motherhood can be a cost for the firm primarily in terms of absences from work. Then, motherhood is a competitive disadvantage among individuals with same characteristics.
I calculate the inverse Mill's ratio by using the following function
$\lambda_F(Z\gamma)=\dfrac{\phi(Z\gamma)}{\Phi(Z\gamma)}$ where $\phi$ and $\Phi$ are for respectively the probability density function and the cumulative distribution function. After, I estimate the wage equation with selection term for females
$Y_{iF}=X_{iF}'\beta_F+\alpha_F\lambda_{iF}+\mu_{iF}$
with $\alpha_F=(\sigma_\mu\rho)$, where $\sigma_\mu$ is the standard deviation of residual term $\mu$ that is normally distributed with mean equal to zero and constant variance equal to $\sigma_\mu^{\ 2}$, and $\rho=corr(\nu,\mu)$ indicates the correlation between two residual terms $\nu$ and $\mu$. Again the independent variables are: *age*, *human capital*, *full-time*, *job position*. The selection effect is significant if there is a correlation between two residual terms. If the coefficient of lambda $\alpha_F$ is positive (negative), there is a positive (negative) correlation. This means that women have wages higher (lower) than the potential wage of women remained outside from labour market, if they had worked. In other words, positive (negative) coefficient means that women with higher probability to be employed have, on average, higher (lower) individual characteristics not linked wit wage. Only in the case of a positive sign, the market mechanisms are meritocratic because there is a negative selection that penalises the women that are the most deserving (see Zorlu, 2003). Regarding the impacts of dependent variables, the dummy *full-time* is the most relevant, followed by the variables *job position*, *human capital*, *age*. (see table D5 in appendix)
Decomposition with the inverse Mill'sratio is the following
$G=[E(X_{iM}-X_{iF})]'\beta_F+E(X_{iF})(\beta_M-\beta_F)+[E(X_{iM}-X_{iF})]'(\beta_M-\beta_F)+\delta\lambda_{iF}$ .
In this case, the gender pay gap is composed of four terms $G=C+R+I+S$ .
The first three terms are the same ones of previous model without adjustment (characteristics effect, returns effect and interaction effect), while the fourth term is the selection effect.[3] The gender pay gap is about 12 percent and it is significant at 1 percent. The average wage for males is around 1,372 euro, as in the previous model without selection, while that of females is about 1,204 euro, more than female's wages in the previous model. As far as features in general terms, the characteristics effect is not significant, but is significant for age (with a negative sign) and dummy of full-time respectively 5 and 1 per cent. Finally, also the returns effect is not significant in general terms, but it is significant for dummy *full-time* at 5 per cent. The returns effect is approximately 37 percent. Finally, the interaction effect is significant at 10 percent as a whole, while the effect referring to full-time dummy is significant at the 5 per cent. The analysis seems to differ little from the unadjusted model, apart from reducing the pay gap.

**Table 2. Blinder-Oaxaca decomposition with selection: OLS model**

| | | | | |
|---|---|---|---|---|
| n. of observations tot. | 344 | | | |
| n. of observations males | 154 | | | |
| n. of observations females | 190 | | | |
| **dip. variable = wage** | **Coef.** | **Std. Err.** | **z** | **P>\|z\|** |
| **standard model without selection** | | | | |
| males | 7.224 | 0.030 | 240.570 | 0.000 |
| females | 6.958 | 0.029 | 241.340 | 0.000 |
| difference (M-F) | 0.266 | 0.042 | 6.390 | 0.000 |
| **model with selection** | | | | |
| males | 7.224 | 0.030 | 240.570 | 0.000 |
| females | 7.093 | 0.061 | 117.180 | 0.000 |
| difference (M-F) | 0.131 | 0.068 | 1.940 | 0.053 |
| characterstics effect | 0.033 | 0.028 | 1.160 | 0.247 |
| returns effect | 0.048 | 0.066 | 0.730 | 0.467 |
| interaction effect | 0.050 | 0.027 | 1.880 | 0.061 |
| *characteristics effect* | | | | |
| age | -0.022 | 0.011 | -1.940 | 0.053 |
| human capital | -0.016 | 0.010 | -1.560 | 0.118 |
| fulltime | 0.083 | 0.018 | 4.510 | 0.000 |
| job position | -0.012 | 0.010 | -1.170 | 0.241 |
| *coefficients effect* | | | | |
| age | 0.058 | 0.227 | 0.260 | 0.798 |
| human capital | -0.064 | 0.135 | -0.470 | 0.636 |
| fulltime | 0.138 | 0.066 | 2.100 | 0.036 |
| job position | -0.079 | 0.112 | -0.710 | 0.480 |
| constant | -0.006 | 0.279 | -0.020 | 0.984 |
| *interaction effect* | | | | |
| age | -0.002 | 0.009 | -0.250 | 0.799 |
| human capital | 0.003 | 0.008 | 0.460 | 0.648 |
| fulltime | 0.045 | 0.023 | 1.970 | 0.049 |
| job position | 0.004 | 0.006 | 0.620 | 0.538 |

Coef.: coefficients; Std. Err.: standard error ; t: t-Student; P > t: p-value; [95% Conf. Interval]: interval of confidence.

3 The selection effect is not reported in the outcome of the regressions, according to the software STATA.

## 5. THE MACHADO-MATA DECOMPOSITION.

By previous models I have estimated the average gender pay gap, while in this paragraph with quantile regressions (Koenker e Bassett, 1978; Buchinsky, 1998 Machado and Mata 2005) I calculate the gender pay gaps along the quantile distribution of wages, in particular quantiles 10th, 25th, 50th, 75th, 90th. I estimate the quantile of monthly wages Y conditioned to the following independent variables X: *age*, *human capital*, *fulltime*, *job position*. Thus, I estimate the following quantile regression $Y_{ij} = X'_{ij}\,\beta_{qj} + u_{iqj}$ where *i* is the individual, *j* is the group (males, females and total population)and *q* is the specific. In order to estimate the vector of coefficients $\beta_q$ , I have to solve the following operation

$$\hat{\beta}_q = \arg\min_{\beta(q)} n^{-1} \sum_{i=1}^{n} \rho_q (Y_i - X'_i\,\beta_q)$$

where $\rho_q(u) = \theta u$ for $u_i \geq 0$ , and $\rho_q(u) = (q-1)u$ for $u < 0$ . According to Buchinsky, 1998, the advantages of this method are: to provide robust estimates of the coefficient vector, which make them insensitive to outliers in the independent variable; an estimation more efficient of OLS model when the errors are not normally distributed; to make clear the effect of independent variables on dependent variable throughout its distribution. Following the method Buchinsky (1998), for each quantile I estimate the full variance-covariance matrix of the coefficients by the method of bootstrapping, in which estimates of the quantiles are carried out simultaneously. Let us analyse the trends of explanatory variables along the distribution coefficients for the three collective (males, females and total), (see tables E1, E2, E3 in appendix)

For the total population, the effect of *age* is always significant at 5 percent up to the fiftieth quantile, and successively it is significant at 1 per cent, and remains stable along the wage distribution. The effect of *human capital* is significant in the 10th quantile at 10 percent and after at 1 per cent, and its impact seems to be constant throughout the wage distribution. The effect of *full-time* dummy is always significant at 1 percent and positive, and decreasing along the wage distribution. The effect of *job position* is not significant in the 10th quantile, and after it becomes significant at 1 percent and is increasing along the wage distribution. Finally, the coefficient of the dummy *female* is always significant and negative, with a non-linear dynamic. In fact, the two highest values concern the 75th and the 10th quantile. With reference to Mincerian equation of males, the effect of *age* is significant and positive and increasing along the wage distribution. The effect of *human capital* is not significant in the 10th quantile, while successively there is a positive and increasing trend. The effect of full-time is not significant in the 10th quantile, while after it becomes significant, positive and decreasing. The effect of *job position* is significant and positive only in the 75th and 90th quantiles, with increasing values (in the 75th quantile values are more than twice the values at the 90th quantile).

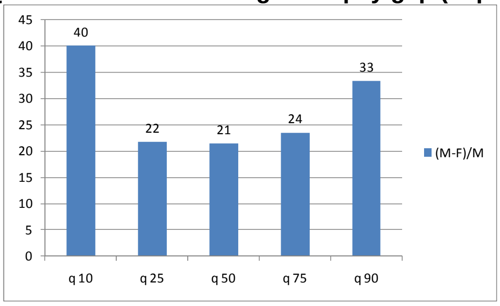
Regarding the collective females, the effect of *age* is significant only in the 75th and 50th quantile, where is positive. The effect of *human capital* is always significant and positive and potentially increasing, with the highest value on the 90th quantile. The effect of *full-time* dummy is always significant and positive, and is decreasing. The effect of *job position* has a level of significance decreasing; in fact, in the first two quantiles 10th and 25th is significant at 1 percent, on the 50th quantile becomes significant at 10 percent, and successively become insignificant.

Let us do quantile decomposition with Machado Mata (2005) model adapted by Melly (2006; 2007) (see also Albrecht et al. 2003) according to which there is the following quantile gender pay gap

$$E(Y_{iF}) - E(Y_{iM}) = -G_q = [E(X_{iF} - X_{iM})]'\beta_{qM} + E(X_{iF})(\beta_{qF} - \beta_{qM}).$$

According to results, as several empirical studies show, the gender pay gap varies along wage distribution. It is always significant and it has a U-shaped pattern (Addabbo T. and Favaro D. 2007). In particular, in the 10th quantile the gender pay gap is 40 percent, in the 90th quantile is equal to 33 percent, while in the intermediate quantiles, 25th, 50th and 75th, is equal respectively to 22, 23 and 21 percent. The initial peak confirms the phenomenon of *sticky floor* according to which there is a peak in the gender pay gap in the lowest quantile (Booth 2003). The final peak indicates the phenomenon of the *glass ceiling*, whereby women have invisible and impenetrable barriers in order to achieve high job position and when they are in these positions earn wages lower than those of males (Maria Cristina Bombellli 2001; Linda S. Austin 2003; L. Wirth 2001; J.D. Dingell, C.B. Maloney 2002). The characteristics effect is significant only in the first two quantiles (10th and 25th) with decreasing trend, after it becomes insignificant. The returns effect is always significant, but it tends to be decreasing with a U dynamic. This effect is the predominant cause of gender pay gap. In fact, in the 10th and 25th it explains respectively about the 49 and 84 percent of gender pay gap, and after it remains the only cause of the gap due to the insignificance of characteristics effect.

**Figure 1 Quantile distribution of gender pay gap (in percentage)**



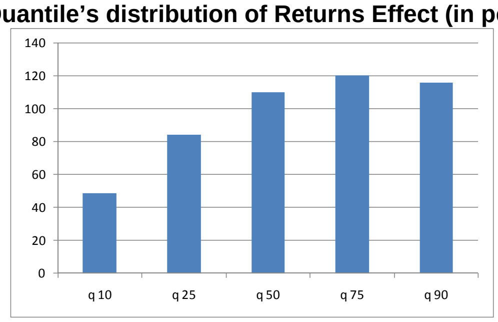

M: males; F: females, q: quantile

**Table 3. Quantile decomposition.**

| | | | | |
|---|---|---|---|---|
| n. of observations tot. | 344 | | | |
| n. of observations males | 154 | | | |
| n. of observations females | 190 | | | |
| **dip. variable = income** | **Coef.** | **Std. Err.** | **z** | **P>\|z\|** |
| | **10th quantile** | | | |
| difference (F-M) | -0.461 | 0.053 | -8.750 | 0.000 |
| characterstics effect | -0.237 | 0.061 | -3.900 | 0.000 |
| returns effect | -0.224 | 0.058 | -3.860 | 0.000 |
| | **25th quantile** | | | |
| difference (F-M) | -0.255 | 0.052 | -4.890 | 0.000 |
| characterstics effect | -0.040 | 0.029 | -1.370 | 0.054 |
| returns effect | -0.215 | 0.021 | -10.390 | 0.000 |
| | **50th quantile** | | | |
| difference (F-M) | -0.135 | -24759.000 | 5.470 | 0.000 |
| characterstics effect | 0.014 | 31534.000 | 0.440 | -0.615 |
| returns effect | -0.149 | -27448.000 | 5.440 | 0.000 |
| | **75th quantile** | | | |
| difference (F-M) | -0.152 | 0.025 | -6.120 | 0.000 |
| characterstics effect | 0.031 | 0.028 | 1.110 | 0.257 |
| returns effect | -0.183 | 0.027 | -6.760 | 0.000 |
| | **90th quantile** | | | |
| difference (F-M) | -0.167 | 0.033 | -5.100 | 0.000 |
| characterstics effect | 0.027 | 0.050 | 0.540 | 0.483 |
| returns effect | -0.194 | 0.038 | -5.070 | 0.000 |

F:females; M: males; Std. Err.: standard error; z: critical value; P>z: p-value; [95% Conf. Interval]: interval of confidence. The number of regressions estimated is 100 with boostrapping method

**Figure 2 Quantile's distribution of Returns Effect (in percentage)**

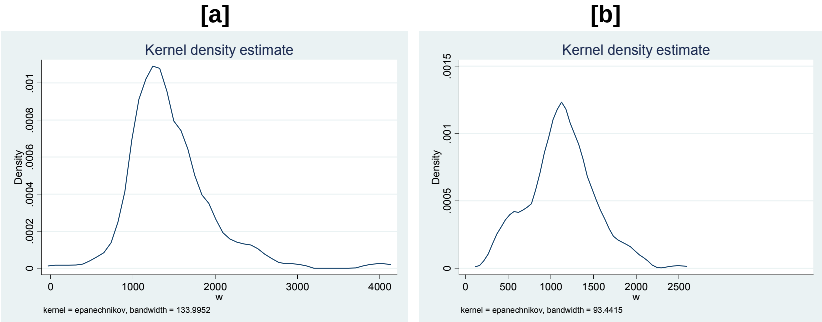



q: quantile.

Finally, let us do a non-parametric analysis of gender pay gap. The following two charts show the distribution of the Epanechnikov Kernel function for the wages of males and females. The graphs show the presence of a positive gender pay gap in favour of males which have a wage distribution more shifted to the right.

**Figure 3. Wages distribution of the Kernel's density function (w) for males [a] and female [b]**

**[a]** **[b]**



## 6.POLICY IMPLICATIONS

According the results, women need for policies that enable them to combine work life and family life. "Reconciliation policies can be defined as policies that directly support the combination of professional family and private life. As such they may refer to a wide variety of policies ranging from childcare services, leave facilities, flexible working arrangements and other reconciliation policies such as financial allowances for working partners" (European Commission 2008 p.20, see also Plantenga, J. and Remery, C. 2005). For example, a greater opportunity of part-time jobs could increase the female participation to labour market (Del Boca 2002). Such reconciliation policies must be carefully evaluated and in case of adverse impact should be amended and restated in the most appropriate way, given the complexity of the social, cultural, economic and institutional context (Plantenga , J., Remery, C. and Rubery, J. (2007). In Northern European countries, characterised by a high supply of social services concerning the care of children and elders, the gender gap in terms of employment is low. This fact confirms the effectiveness of these policies (Ginn 2004).

In terms of gender policies in the labour market, results confirm that young adult people need for moving the attention from the goal of "gender equality" to the goal of "gender mainstreaming" defined as "the (re) organization, improvement, development and evaluation of policy processes, so as to incorporate a gender perspective in all policies at all levels and at all stages by all the parties involved usually the political conception" (Council of Europe 1998, p.12). These policies should be composed of specific strategies (European Commission 2008). The first is the *tinkering* (patching) which consists of measures to establish a formal equality between genders, for example in terms of wages or access to the labour market. The second strategy is the *tailoring* (custom fit); it covers all those measures which permit to improve equality of real opportunities, such as policies to support women to care for children. Finally, the strategy characterising gender mainstreaming is the *transforming strategy* according to which policies aim to change the *status quo* through innovative proposals that offer new tools suitable for transforming the social, economic and even cultural turning in favour of females. In line with this strategy, the active policy of gender in the labour market tend to increase the probability of employment and/or improve income opportunities for women through specific actions such as training, job rotation and sharing of work, incentives to employment, direct creation of jobs and business start-up incentives. (European Commission 2006) Finally it should be noted that policies against gender inequality in the labour market are also useful in the future of pensions. In fact, the pension reforms affecting most European countries tend to strengthen the link between contributions and pension benefits. Thereby there could be the risk that the current gender pay gap will be transformed into the expected pension gender gap. (Horstmann S. and J. Hüllsman, 2009)

## 7.CONCLUSION

I have aimed to investigate the causes of gender pay gap among Italian young adults. I estimated three econometric models: Blinder-Oaxaca standard model, Blinder-Oaxaca model with selection, the Machado Mata standard model. I have decomposed gender pay gap in two effects: characteristics and returns effects. The former considers gender differences in the individual characteristics, while the latter considers gender differences in the remunerations of the individual characteristics. This last effect can be interpreted as an indicator of discrimination.

According to the results, the gender pay gaps are significant and positive for males. They have a U-shaped pattern along the quantile distribution of wage such as in Addabbo and Favaro (2007). This first result confirms the presence of two relevant phenomena. The first is the *sticky floor* effect, according to which the gender pay gap is high at bottom wage levels and the *glass ceiling* effect, according to which the gender pay gap is high at the top wage levels. According to the results, the sticky floor effect is higher than the glass ceiling effect, because the gender pay gap in the tenth quantile is greater than that one in the ninetieth quantile. This phenomenon could be consistent with the results of the study of Arulampalam et al. (2007), according to which the relation between sticky floor and glass ceiling effect depends on the effectiveness of reconciliation policies. In fact, in the Southern European countries, such as Italy, where these policies are not very effective, the sticky floor effect is predominant, while in the Northern European countries, where such policies are most developed and effective, the main effect is the glass ceiling effect.

The returns effect, that may indicates the existence of gender discrimination, is equal to 69 percent in the Blinder-Oaxaca standard model, and 37 percent in the Blinder-Oaxaca model with selection. This decreasing trend between two models is also confirmed in the analysis of Centra and Cutillo (2009). But the values of this effect are higher than those in studies where the population is aged between 15 and 65 years, such as Centra and Cutillo (2009), and Addabbo and Favaro (2007), in which the percentages are respectively about 15 and 18 percent in models without selection, and, 11 and 16, in models with selection. These different results could indicate that discrimination concerns mainly the young adult women. Thus, young adult females in Italy suffer a double discrimination for being both women and young adults.

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# APPENDIX

## A. Variables'description

### Table A1. Variables' description for total population

| Variable | N. Observations | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| wage | 344 | 1334.927 | 488.1643 | 100 | 4000 |
| age | 344 | 36.41638 | 5.665108 | 25 | 45 |
| human capital | 344 | 4.113859 | 1.205341 | 1 | 6 |
| full time | 344 | 0.8293316 | 0.376767 | 0 | 1 |
| job position | 344 | 1.870014 | 0.6452658 | 1 | 4 |

### Table A2. Variables' description for males

| Variable | N. Observations | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| wage | 154 | 1455.091 | 500.6594 | 100 | 4000 |
| age | 154 | 35.90392 | 6.108949 | 25 | 45 |
| human capital | 154 | 4.029345 | 1.151752 | 2 | 6 |
| full time | 154 | 0.9113593 | 0.2851517 | 0 | 1 |
| job position | 154 | 1.838266 | 0.6943951 | 1 | 4 |

### Table A3 Variables' description for females

| Variable | N. Observations | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| wage | 190 | 1126.92 | 387.7776 | 208 | 2500 |
| age | 190 | 37.30348 | 4.699656 | 26 | 45 |
| human capital | 190 | 4.260155 | 1.284443 | 1 | 6 |
| full time | 190 | 0.6873386 | 0.4648025 | 0 | 1 |
| job position | 190 | 1.92497 | 0.5489742 | 1 | 4 |

## B. Gender analysis of variables

### Table B1. Gender analysis of age's group

| | absolute values | | percentage | |
|---|---|---|---|---|
| age | males | females | males | females |
| 25-29 | 43 | 12 | 27.9 | 6.3 |
| 30-34 | 34 | 26 | 22.1 | 13.7 |
| 35-40 | 32 | 70 | 20.8 | 36.8 |
| 40-45 | 45 | 82 | 29.2 | 43.2 |
| total | 154 | 190 | 100.0 | 100.0 |

### Table B2. Gender analysis for human capital

| | absolute value | | percentage | |
|---|---|---|---|---|
| human capital level | males | females | males | females |
| primary school | 0 | 1 | 0.0 | 0.5 |
| secondary school/junior high | 24 | 25 | 15.6 | 13.2 |
| professional certification | 3 | 7 | 1.9 | 3.7 |
| secondary school/high | 93 | 101 | 60.4 | 53.2 |
| first cycle degree/bachelor | 10 | 8 | 6.5 | 4.2 |
| second sycle degree or single cycle degree(combined bachelor and master)/two year master or PHD | 24 | 48 | 15.6 | 25.3 |
| total | 154 | 190 | 100.0 | 100.0 |

### Table B3. Gender analysis of full-time/part-time

| | absolute value | | percentage | |
|---|---|---|---|---|
| | males | females | males | females |
| part-time | 17 | 63 | 11.0 | 33.2 |
| full-time | 137 | 127 | 89.0 | 66.8 |
| total | 154 | 190 | 100.0 | 100.0 |

### Table B4. Gender analysis of job position

| | absolute value | | percentage | |
|---|---|---|---|---|
| job position | males | females | males | females |
| worker | 44 | 31 | 28.6 | 16.3 |
| servant | 98 | 148 | 63.6 | 77.9 |
| executive | 7 | 6 | 4.5 | 3.2 |
| manager | 5 | 5 | 3.2 | 2.6 |
| total | 154 | 190 | 100.0 | 100.0 |

## C. Blinder-Oaxaca Standard Model

### Table C1. Wage regression: OLS model (total population)

| dip. variable = wage | Coef. | Std. Err. | t | P>\|t\| | N. of observ. | 344 |
|---|---|---|---|---|---|---|
| age | 0.017 | 0.003 | 5.960 | 0.000 | F( 5, 338) | 59.2 |
| human capital | 0.069 | 0.015 | 4.560 | 0.000 | Prob > F | 0.000 |
| fulltime | 0.460 | 0.044 | 10.360 | 0.000 | R-squared | 0.4669 |
| job position | 0.103 | 0.028 | 3.680 | 0.000 | Adj R-squared | 0.459 |
| female | -0.212 | 0.035 | -6.060 | 0.000 | Root-MSE | 0.29388 |
| constant | 5.930 | 0.131 | 45.280 | 0.000 | | |

Coef.: coefficients; Std. Err.: standard error ; t: t-Student; P > t: p-value; [95% Conf. Interval]: interval of confidence.

### Table C2. Wage regression: OLS model (males)

| dip. variable = wage | Coef. | Std. Err. | t | P>\|t\| | N. of observ. | 154 |
|---|---|---|---|---|---|---|
| age | 0.017 | 0.004 | 4.380 | 0.000 | F( 4, 149) | 25.09 |
| human capital | 0.055 | 0.024 | 2.300 | 0.023 | Prob > F | 0.000 |
| fulltime | 0.572 | 0.083 | 6.910 | 0.000 | R-squared | 0.4025 |
| job position | 0.093 | 0.040 | 2.350 | 0.020 | Adj R-squared | 0.3864 |
| constant | 5.683 | 0.183 | 31.090 | 0.000 | Root-MSE | 0.28959 |

Coef.: coefficients; Std. Err.: standard error ; t: t-Student; P > t: p-value; [95% Conf. Interval]: interval of confidence.

### Table C3. Wage regression: OLS model (females)

| dip. variable = wage | Coef. | Std. Err. | t | P>\|t\| | N. of observ. | 190 |
|---|---|---|---|---|---|---|
| age | 0.015 | 0.005 | 3.160 | 0.002 | F( 4, 185) | 37 |
| human capital | 0.092 | 0.019 | 4.910 | 0.000 | Prob > F | 0.000 |
| fulltime | 0.374 | 0.048 | 7.870 | 0.000 | R-squared | 0.4444 |
| job position | 0.135 | 0.043 | 3.150 | 0.002 | Adj R-squared | 0.4324 |
| constant | 5.501 | 0.199 | 27.620 | 0.000 | Root-MSE | 0.29725 |

Coef.: coefficients; Std. Err.: standard error ; t: t-Student; P > t: p-value; [95% Conf. Interval]: interval of confidence.

## D. The Blinder-Oaxaca model with selection

### Table D1. Description of Variables (females).

| Variable | N. Observations | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| employee | 521 | 0.632 | 0.483 | 0 | 1 |
| children | 521 | 0.802 | 0.399 | 0 | 1 |
| human capital | 521 | 4.058 | 1.390 | 1 | 6 |
| north | 521 | 0.475 | 0.500 | 0 | 1 |

### Table D2. Employment status (females)

| status | absolute value | percentage |
|---|---|---|
| non-employee | 192 | 36.9 |
| employee | 329 | 63.1 |
| total | 521 | 100.0 |

### Table D3. Life status (females)

| status | absolute value | percentage |
|---|---|---|
| without children | 102 | 19.6 |
| with children | 419 | 80.4 |
| total | 521 | 100.0 |

### Table D4. Occupation regression: Probit model (females)

| dip. variable = employee | Coef. | Std. Err. | t | P>\|t\| | N. of observ. | 521 |
|---|---|---|---|---|---|---|
| children | -0.382 | 0.157 | -2.430 | 0.015 | LR chi2(3) | 62.19 |
| human capital | 0.157 | 0.042 | 3.720 | 0.000 | Prob > chi2 | 0.000 |
| north | 0.751 | 0.120 | 6.270 | 0.000 | Pseudo $R^2$ | 0.0907 |
| constant | -0.290 | 0.241 | -1.200 | 0.229 | | |

Coef.: coefficienti; Std. Err.: errore standard; z: valore soglia; P>z: p-value; [95% Conf. Interval]: intervallo di confidenza.

### Table D5. Wage regression: OLS model with selection (females)

| dip. variable = income | Coef. | Std. Err. | t | P>\|t\| | N. of observ. | 190 |
|---|---|---|---|---|---|---|
| age | 0.016 | 0.005 | 3.450 | 0.001 | F( 5, 184) | 31.7 |
| human capital | 0.070 | 0.020 | 3.440 | 0.001 | Prob > F | 0.000 |
| fulltime | 0.371 | 0.047 | 7.890 | 0.000 | R-squared | 0.4628 |
| job position | 0.134 | 0.042 | 3.170 | 0.002 | Adj R-squared | 0.4482 |
| Mill's ratio | -0.259 | 0.103 | -2.510 | 0.013 | Root-MSE | 0.29309 |
| constant | 0.210 | 27.070 | 0.000 | 5.274 | | |

Coef.: coefficients; Std. Err.: standard error ; t: t-Student; P > t: p-value; [95% Conf. Interval]: interval of confidence.

## E. Machado-Mata Standard Model

### Table E1. Wage regression: quantile model (total population)

| n. of observations tot. | 344 | | .50 Pseudo $R^2$ | 0.2777 |
|---|---|---|---|---|
| .10 Pseudo $R^2$ | 0.368 | | .75 Pseudo $R^2$ | 0.2741 |
| .25 Pseudo $R^2$ | 0.3208 | | .90 Pseudo $R^2$ | 0.2741 |
| **dip. variable = income** | **Coef.** | **Std. Err.** | **z** | **P>\|z\|** |
| | **10th quantile** | | | |
| age | 0.011 | 0.005 | 2.160 | 0.032 |
| human capital | 0.070 | 0.040 | 1.780 | 0.076 |
| fulltime | 0.617 | 0.099 | 6.210 | 0.000 |
| job position | 0.055 | 0.064 | 0.860 | 0.390 |
| female | -0.216 | 0.107 | -2.020 | 0.044 |
| constant | 5.610 | 0.350 | 16.010 | 0.000 |
| | **25th quantile** | | | |
| age | 0.013 | 0.006 | 2.120 | 0.035 |
| human capital | 0.066 | 0.023 | 2.830 | 0.005 |
| fulltime | 0.556 | 0.061 | 9.110 | 0.000 |
| job position | 0.089 | 0.023 | 3.940 | 0.000 |
| female | -0.169 | 0.051 | -3.320 | 0.001 |
| constant | 5.637 | 0.264 | 21.320 | 0.000 |
| | **50th quantile** | | | |
| age | 0.013 | 0.004 | 3.150 | 0.002 |
| human capital | 0.067 | 0.018 | 3.770 | 0.000 |
| fulltime | 0.458 | 0.060 | 7.640 | 0.000 |
| job position | 0.082 | 0.033 | 2.460 | 0.014 |
| female | -0.161 | 0.049 | -3.260 | 0.001 |
| constant | 5.882 | 0.204 | 28.810 | 0.000 |
| | **75th quantile** | | | |
| age | 0.015 | 0.005 | 3.280 | 0.001 |
| human capital | 0.059 | 0.019 | 3.130 | 0.002 |
| fulltime | 0.292 | 0.045 | 6.530 | 0.000 |
| job position | 0.149 | 0.052 | 2.870 | 0.004 |
| female | -0.232 | 0.039 | -5.930 | 0.000 |
| constant | 6.039 | 0.145 | 41.760 | 0.000 |
| | **90th quantile** | | | |
| age | 0.017 | 0.006 | 2.750 | 0.006 |
| human capital | 0.066 | 0.022 | 2.980 | 0.003 |
| fulltime | 0.299 | 0.071 | 4.240 | 0.000 |
| job position | 0.160 | 0.045 | 3.540 | 0.000 |
| female | -0.167 | 0.069 | -2.400 | 0.017 |
| constant | 6.010 | 0.236 | 25.430 | 0.000 |

Simultaneous quantile regression bootstrap(10) SEs, Pseudo R2: for each quantile Coef.: coefficients; Std. Err.: standard error ; t: t-Student; P > t: p-value; [95% Conf. Interval]: interval of confidence.

### Table E2. Wage regression: quantile model (males)

| n. of observations tot. | 154 | | .50 Pseudo $R^2$ | 0.2531 |
|---|---|---|---|---|
| .10 Pseudo $R^2$ | 0.3276 | | .75 Pseudo $R^2$ | 0.2731 |
| .25 Pseudo $R^2$ | 0.2557 | | .90 Pseudo $R^2$ | 0.2736 |
| **dip. variable = income** | **Coef.** | **Std. Err.** | **z** | **P>\|z\|** |
| | **10th quantile** | | | |
| age | 0.009 | 0.004 | 2.450 | 0.016 |
| human capital | 0.000 | 0.022 | 0.000 | 1.000 |
| fulltime | 0.650 | 0.817 | 0.800 | 0.428 |
| job position | 0.022 | 0.047 | 0.460 | 0.647 |
| constant | 5.976 | 0.843 | 7.090 | 0.000 |
| | **25th quantile** | | | |
| age | 0.016 | 0.003 | 4.650 | 0.000 |
| human capital | 0.436 | 0.038 | 1.140 | 0.257 |
| fulltime | 0.519 | 0.122 | 4.260 | 0.000 |
| job position | 0.024 | 0.032 | 0.740 | 0.463 |
| constant | 5.779 | 0.236 | 24.520 | 0.000 |
| | **50th quantile** | | | |
| age | 0.015 | 0.004 | 3.480 | 0.001 |
| human capital | 0.064 | 0.028 | 2.290 | 0.024 |
| fulltime | 0.465 | 0.109 | 4.280 | 0.000 |
| job position | 0.062 | 0.052 | 1.190 | 0.234 |
| constant | 5.853 | 0.236 | 24.800 | 0.000 |
| | **75th quantile** | | | |
| age | 0.015 | 0.005 | 2.900 | 0.004 |
| human capital | 0.052 | 0.023 | 2.200 | 0.029 |
| fulltime | 0.300 | 0.080 | 3.740 | 0.000 |
| job position | 0.165 | 0.034 | 4.890 | 0.000 |
| constant | 6.040 | 0.223 | 27.090 | 0.000 |
| | **90th quantile** | | | |
| age | 0.018 | 0.005 | 3.380 | 0.001 |
| human capital | 0.035 | 0.015 | 2.290 | 0.023 |
| fulltime | 0.353 | 0.089 | 3.950 | 0.000 |
| job position | 0.160 | 0.068 | 2.360 | 0.019 |
| constant | 6.068 | 0.181 | 33.500 | 0.000 |

Simultaneous quantile regression bootstrap(10) SEs, Pseudo R2: for each quantile Coef.: coefficients; Std. Err.: standard error ; t: t-Student; P > t: p-value; [95% Conf. Interval]: interval of confidence.

**Table E3. Wage regression: quantile model (females)**

| | | | | |
|---|---|---|---|---|
| n. of observations tot. | 190 | | .50 Pseudo $R^2$ | 0.2816 |
| .10 Pseudo $R^2$ | 0.3765 | | .75 Pseudo $R^2$ | 0.2351 |
| .25 Pseudo $R^2$ | 0.3642 | | .90 Pseudo $R^2$ | 0.2416 |
| **dip. variable = income** | **Coef.** | **Std. Err.** | **z** | **P>\|z\|** |
| **10th quantile** | | | | |
| age | 0.016 | 0.015 | 1.120 | 0.264 |
| human capital | 0.088 | 0.016 | 5.510 | 0.000 |
| fulltime | 0.665 | 0.086 | 7.700 | 0.000 |
| job position | 0.240 | 0.037 | 6.520 | 0.000 |
| constant | 4.724 | 0.566 | 8.350 | 0.000 |
| **25th quantile** | | | | |
| age | 0.008 | 0.007 | 1.190 | 0.234 |
| human capital | 0.089 | 0.015 | 5.880 | 0.000 |
| fulltime | 0.578 | 0.066 | 8.730 | 0.000 |
| job position | 0.169 | 0.012 | 13.670 | 0.000 |
| constant | 5.387 | 0.328 | 16.410 | 0.000 |
| **50th quantile** | | | | |
| age | 0.011 | 0.005 | 1.950 | 0.053 |
| human capital | 0.073 | 0.010 | 7.050 | 0.000 |
| fulltime | 0.433 | 0.069 | 6.310 | 0.000 |
| job position | 0.108 | 0.060 | 1.800 | 0.073 |
| constant | 5.767 | 0.262 | 22.050 | 0.000 |
| **75th quantile** | | | | |
| age | 0.015 | 0.004 | 3.720 | 0.000 |
| human capital | 0.064 | 0.026 | 2.500 | 0.013 |
| fulltime | 0.278 | 0.092 | 3.030 | 0.003 |
| job position | 0.124 | 0.078 | 1.580 | 0.116 |
| constant | 5.838 | 0.166 | 35.120 | 0.000 |
| **90th quantile** | | | | |
| age | 0.009 | 0.007 | 1.180 | 0.241 |
| human capital | 0.107 | 0.044 | 2.430 | 0.016 |
| fulltime | 0.197 | 0.095 | 2.080 | 0.039 |
| job position | 0.137 | 0.096 | 1.420 | 0.157 |
| constant | 6.114 | 0.234 | 26.090 | 0.000 |

Simultaneous quantile regression bootstrap(10) SEs, Pseudo R2: for each quantile Coef.: coefficients; Std. Err.: standard error ; t: t-Student; P > t: p-value; [95% Conf. Interval]: interval of confidence.