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The gender wage gap among PhD holders: an empirical examination based on Italian data.

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Abstract: A growing number of academic studies are devoting their attention to the study of the gender wage gap. This paper contributes to the literature by analyzing the existence of this gap specifically among those who hold the highest possible educational qualification, i.e. a PhD. The analysis relies on Italian cross-sectional data collected through a highly representative survey of the employment conditions of PhD holders. The econometric analysis is carried out by means of OLS regression, Oaxaca-Blinder decomposition analysis and quantile decomposition. Findings suggest that a gender gap in hourly wages exists among PhD holders, that it lies approximately between 5% and 8%, with sizeable differences by sector of employment and field of specialization, and that such a gap is largely unexplained.

Keywords: gender wage gap; return on education, Oaxaca-Blinder decomposition; quantile decomposition

JEL codes: J31, J71

1. Introduction

Although much progress has been made in reducing gender inequality, this issue remains crucial for contemporary societies and continues to occupy a prominent place in the political agenda of many governments. The EU considers equality between women and men both a fundamental right and an essential feature of stable and transparent democracies (European Commission, 2018). It has recently put effort into the elaboration of a strategy specifically devoted to fostering it (European Union, 2015). Part of this strategy focuses on fighting gender economic inequality and, more specifically, inequality of wages.¹

The gender gap in wages has drawn attention from academics and policy analysts for some time (for a systematic review of previous studies, see Bishu & Alkadry, 2017). The systematic difference in wages between men and women is recognized as a moral and socio-economic issue per se, and is identified as a specific form of workplace discrimination, which reveals the lower access to resources and opportunities that women experience in the labour market.

Existing studies highlight the close links between the wage gap and education. On the one hand, gender differences in educational level and fields of study tend to exclude women from the best paid jobs (Bobbitt-Zeher, 2007; European Commission, 2005). On the other hand, the literature highlights that in European countries gender differences in returns from education are also observed, i.e. gender wage gaps also exist among people with the same level of education, even if differentials are lower among the highly educated (de la Rica et al., 2008; Garcia-Prieto & Gómez-Costilla, 2017; Mussida & Picchio, 2014).

This paper contributes to the existing literature by proposing an empirical analysis of the gender wage gap among PhD holders specifically. Focusing on workers who have completed doctoral studies is particularly valuable for the gender gap literature since it allows us to check whether a differential in wages persists even among those who have attained the highest possible educational level. Furthermore, this analysis is potentially useful for the literature on the occupational outcomes of doctorate holders, which have undoubtedly become more extensive in recent years, fostered by the crucial role in the promotion of innovation and economic growth that is attributed to PhD workers (Auriol et al., 2012).

To the best of our knowledge, the only existing paper that focuses specifically on the gender wage gap among PhD holders is Webber and Canché (2015). Their study relies on US data, and finds evidence of a significant gap. Other existing contributions do not specifically address the issue of wage gaps among PhD holders, even if they do examine the gender gap in doctorate holders' progression in academic careers (Tao, 2018; Webber & Canché, 2015).

¹ The remaining areas refer to equality in decision-making, ending gender-based violence, and promoting gender equality beyond the EU (European Commission, 2018).

The present paper enriches the existing literature by analysing data from Italy, which is an interesting case study for two reasons. First, this country is characterized by a high gender wage gap that, according to a recent contribution, is observed even among university graduates, albeit with marked differences between fields of study (Piazzalunga, 2018). Second, studies suggest that in this country PhD holders' socio-economic potential is not fully exploited, since doctorate holders frequently report over-education and job dissatisfaction (Gaeta, 2015; Gaeta et al, 2017; Pinto & Sarno, 2018). It makes sense to investigate whether the picture is also characterized by a gender difference in occupational outcomes.

Our analysis employs cross-sectional data collected by the Italian National Institute of Statistics (ISTAT) in a survey of PhD holders who completed their studies in 2004 and 2006 and were interviewed a few years after graduation. The use of this data allows us to analyse the gender gap in wages by considering both PhD holders still working in the academic sector and those who have experienced intersectoral mobility (i.e. a shift to non-academic work). The focus on recent graduates is valuable because it allows us to focus the analysis on wage differentials that are not severely affected by gaps in working experience.

The empirical investigation relies on OLS regressions, Oaxaca-Blinder decomposition and quantile decomposition. Our results reveal that a gender wage gap exists even among PhD holders. According to our estimates based on Italy, such a gap ranges between 4.9% and 6.7%, which is in line with the estimates provided by the literature focusing on university graduates (5.6%, Piazzalunga, 2018). Most of the discrimination seems to depend on different returns between men and women.

The paper is organized as follows. Section two provides evidence of the importance of the issue of the gender wage gap in Europe and Italy, and briefly reviews the scholarly contributions on the link between education and the wage gap. Section three describes both the data used in the present study and the econometric approach adopted to analyse them. Section four presents and discusses our results. Section five assesses the heterogeneity of our results according to the scientific area of specialization of PhD holders, their sector of employment and their area of residence. Finally, section six concludes.

2. The gender wage gap in Italy and the role of education

A notable reduction of the gender gap in wages in all the economically advanced countries is observed when looking at data in the long run (Blau & Kahn, 2008). Nevertheless, the gap has been proven to still exist (Bishu & Alkadry, 2017; Jarrell & Stanley, 2004; Stanley & Jarrell, 1998; Weichselbaumer & Winter-Ebmer, 2005).

By analysing US data, Blau and Kahn (2017) noticed that the intensity of convergence between men and women's wages achieved high levels in the 1980s, only to decrease in the 1990s. A similar trend was observed

across most of OECD countries (Flabbi, 2012). Weichselbaumer and Winter-Ebmer (2005) observed that in industrialized countries the wage gap decreased from 65% in the 1960s to 30% in the 1990s. Looking at the EU, data from the *Structure of Earning Survey* by Eurostat reveal that in 1995 the unadjusted gender gap for full-time workers was 25% (European Commission, 2005), while more recent information suggests that in the EU-27 over the period 2010-2016, women's hourly wages were approximately 16% lower than those reported by men, even if there is significant regional heterogeneity in this gap (European Commission, 2018).

Looking specifically at the Italian data, in 2014² the overall gender earning gap – calculated by Eurostat (2019) by considering the average earnings per hour, the numbers of hours worked per month and the employment rate – was found to be higher than the EU-28 average (43.7% vs 39.6%).³ As previous studies have pointed out, one of the main factors affecting the gender wage gap in Italy is selection into the workforce and discrimination in workforce participation (Mussida & Picchio, 2014). A peculiar trait of the Italian case is involuntary part-time employment, which reached 60.8% among women in 2018, a figure significantly higher than the European mean value (22.1%) (Eurostat 2019b).⁴ Furthermore, in 2018 the employment rate reveals important differences between men (67.5%) and women (49.6%) compared to the EU average (74.1% vs 63.6%) (Eurostat, 2019).

In line with the scientific literature (Alkadry & Tower, 2006; Arulampalam et al., 2007; Lin & Gunderson, 2014; Miller, 2009), recent research has explored the gender wage gap, paying specific attention to those factors that help to explain the extent and drivers of the wage gap: namely, occupational and sectorial segregation (Rebérioux & Roudaut, 2019) and educational attainment.

Starting from Katz and Murphy (1992), who pointed out the importance of education in occupational opportunities and related earning capacities, other scholars have focused on the relation between the wage gap and education (Blau & Kahn, 2008; de la Rica et al., 2008; Kolesnikova & Liu, 2011; Montgomery & Powell, 2003).

Two papers have explored this issue in Italy specifically: Addabbo and Favaro (2011) observe that the wage gap is higher at low educational attainment and detect the existence of a “glass ceiling” effect only for highly educated workers; Mussida and Picchio (2014) find a larger wage penalty and some evidence of a “sticky floor” among less educated workers. A more recent contribution is provided by Piazzalunga (2018), who analyses a sample of Italian university graduates and detects a gender wage gap of 5.6% that is almost completely unexplained by observable characteristics. The author stresses the importance of the field of study as explanatory variable, observing on the one hand an under-representation of women in fields offering the highest wage prospects, such as maths-sciences and engineering; on the other hand, she finds evidence of the largest total gap in law, political and social sciences and economics-statistics (Piazzalunga, 2018).

² The latest year available from the Eurostat Database on gender equality.

³ In the Euro Area (19 countries) the average value for 2014 is 40.6% (Eurostat, 2019).

⁴ Men also show higher percentages compared to the EU average.

Furthermore, some evidence of a “glass ceiling” effect is provided. The fact that the gender wage gap estimated for recent graduates is similar to the one estimated for the wider population challenges the idea that wage discrimination decreases as educational attainment increases. This paper aims to contribute to this debate by determining whether any wage gap is detected among PhD holders.

3. Data and methodology

3.1 Data

Our main data source is the first edition of the “Survey on the employability of PhD holders” (*“Indagine sull’inserimento professionale dei Dottori di Ricerca”*) carried out by ISTAT in 2010. This cross-sectional survey investigates the early stage career outcomes reported by individuals who obtained a PhD in Italy in 2004 and 2006 and, therefore, were interviewed 5 and 3 years after graduation, respectively.

The survey was designed to involve the entire population of PhD recipients in the two cohorts considered, who were contacted between December 2009 and February 2010. While part of this population (which included 18,568 PhD holders, 8,443 of whom graduated in 2004 and 10,125 in 2006) did not reply, the final response rate reported by the survey (69.65%) makes it highly representative of the population under scrutiny. The final sample includes 8,814 observations: 3,928 refer to PhD holders who graduated in 2004, while 4,886 refer to those from the 2006 cohort.

The ISTAT survey includes a wide set of data valuable for our analysis insofar as they identify the wage of respondents as well as individual-level features that might exert some influence on their career choice and/or on their wage.

Our main variable of interest is the log of net hourly wage. Unfortunately, ISTAT only records the net monthly wage. However, it does report the number of weekly hours devoted to work. We used this information to estimate the log of hourly wages by taking the natural logarithm of the monthly wage multiplied by 12 and divided by the number of hours worked per hour multiplied by 52. In formal terms:

$$HWage = \log \log \frac{MonthlyWage * 12}{WeeklyHours * 52}$$

Some of the interviewed PhD holders did not answer the survey question concerning their earnings. More specifically, 864 observations (approximately 10% of the full sample) report a missing value for the variable that records their hourly wage. For most of them (approximately 7%) the reason was unemployment. These observations were dropped from the sample and our final dataset therefore includes 7,950 individuals.

Individual features that might exert some impact on the reported wages might be grouped as follows:

A first set of variables (labelled *Back*) allows us to observe the respondents' background. There are four of them. The first is a dummy (labelled *PhDin2006*) that takes the value of 1(0) for those belonging to the 2006 (2004) cohort under scrutiny; the second is a dummy (labelled *ParentDegree*) equal to 1 if the highest level of education acquired by a respondent's parents is at least a degree; the third is a dummy (labelled *Orphan*) equal to 1 if the interviewee has no living parent; finally, one dummy (labelled *DPA*) is equal to 1 if the former PhD student is now working in the public sector.

A second set of variables (*Demo*) concerns socio-demographic characteristics. This set includes one dummy (*Married*) equal to 1 if the respondent is married; one dummy (*LivAlone*) equal to 1 if the interviewee lives alone; one dummy (*Children*) equal to 1 if the interviewee has a son or a daughter, and two dummies identifying the geographical area of Italy in which he or she lives (*Northern Italy* and *Southern Italy*).

The third set of variables (*Job*) regards job features. A first variable in this set observes respondents' years of employment in their current career (*Tenure*). It is worth noting that the tenure variable unfortunately reports a high number of missing values (2,891, 32.80% of the sample). Thus, the regression in which this variable is included reports a lower amount of observations. Alongside this variable, dummies allow us to identify those who work in the service sector (*Services*) or in Industry (*Industry*),⁵ those who work fulltime (*Fulltime*) and those who are self-employed (*PIVA*). Finally, since migration is triggered by one's willingness to obtain better opportunities (e.g. higher wages), we also included one dichotomous variable that takes the value of one for those who declared they worked in an Italian region different from the one where they completed their PhD studies.

The fourth set (*Edu*) allows us to observe features of the PhD and previous studies carried out by respondents. First, dummy variables allow us to identify the high school typology that respondents completed before university (*Classical, Scientific, Linguistic, Pedagogic, Technical, Professional, Artistic*). Second, four dichotomous variables allow us to observe respondents' final grade at the end of their Master's degree. This grade theoretically ranges between 66 and 110 magna cum laude and has been categorized as follows: lower than 101, between 101 and 105, higher than 105, 110 magna cum laude. In addition, PhD-related variables include thirteen dichotomous variables that identify the scientific area in which respondents completed their PhD (from *Area1* to *Area13*⁶), a dummy taking the value of one for those who benefitted from a scholarship

⁵ In order to avoid the dummy trap econometric problem, we decided not to control for other sectors such as *Agriculture, Hunting and Fishing*.

⁶ Areas are: 01 – Mathematics and informatics; 02 – Physics; 03 – Chemistry; 04 – Earth sciences; 05 – Biology; 06 – Medicine; 07 – Agricultural and veterinary sciences; 08 – Civil engineering and architecture; 09 – Industrial and information engineering; 10 – Antiquities, philology, literary studies, art history; 11 – History, philosophy, pedagogy and psychology; 12 – Law; 13 – Economics and statistics; 14 – Political and social sciences.

during their PhD (*Scholarship*), one dummy that identifies those who carried out a visiting period in a foreign country during their PhD (*Visiting*), and another that identifies those who taught lessons during their PhD (*Teaching*). Furthermore, dummies allow us to identify those who completed their PhD within the standard deadline, i.e. within three years (*InTime*). Finally, four additional dummy variables measure the age of respondents at the end of their PhD (*Age<30*, *Age=30*, *Age=31* and *Age>32*).

Table 1 illustrates the basic summary statistics for these variables calculated by gender.

3.2 Methodology

With the aim of inspecting the existence of a gender wage gap, the analysis relies on three different econometric approaches.

At first, the following wage equation is estimated by means of an OLS regression:

$$Y = F\beta_1 + Back\beta_2 + Demo\beta_3 + Job\beta_4 + Edu\beta_4 + u$$

where F is a dummy equal to 1 if the individual is a woman, $Back$, $Demo$, Job and Edu are the sets of controls, and β_1 is the coefficient of interest. Four estimations are performed by progressively including the sets of controls. The main limitation of such an approach is that only one equation is estimated, meaning that the estimated coefficients are the same for both men and women.

In a second stage of the analysis, we apply the Oaxaca-Blinder decomposition to our variables. This technique was originally developed in labour economics, and has since been widely used to analyze the determinants of male/female earnings differentials, as a means to estimate the level of discrimination in the labour market (Blinder, 1973; Oaxaca, 1973). The decomposition essentially assesses how much of a gap is due to the differences in characteristics (explained variation) and how much is due to the same characteristic giving different returns (unexplained variation).

One of the main problems of estimating the performances of different groups of agents by pooling data is that the independent variables are indistinguishable for both groups. We make use of the Oaxaca-Blinder (O-B) decomposition to overcome this limitation and estimate a performance equation separately for the two groups (Blinder 1973; Oaxaca 1973). The idea is to decompose the sources of performance (the points gap) into one component caused by differences in characteristics of the two groups (female and male workers), and into one component caused by differences in returns to the same characteristic across groups (the so-called unexplained component). The general model is:

$$z_g = \beta_g X_g + \varepsilon_g \quad (1)$$

where $g = \{m, f\}$, Xg is the vector of all the explanatory variables, βg is the vector of the coefficients, and εg is the error. However, we estimate the above (without the Italy dummy) separately for female (f) and a pooled set that also includes male (m). In our notation, the O-B decomposition is thus:

$$z_f - z_m = \beta_f X_f - \beta_m X_m = (X_f - X_m)\beta_f + X_m(\beta_f - \beta_m) \quad (2)$$

The first term $(X_f - X_m)$ corresponds to the difference in performance between the two groups (points gap) due to the differences in the characteristics of each group. The second term, meanwhile, corresponds to the unexplained component, due to differences in returns between female and the pooled female-male set. In this family of models, which are principally applied in labour economics, the second term is often labeled “discrimination”, since it provides a measure of the difference in wages that cannot be explained by explicit differences in the characteristics of the two groups. In other terms, this is the relative difference in wages that can be attributed to the unobserved characteristics; in a wider interpretation: all that it is not related to observable characteristics.

The third econometric approach employed here is quantile decomposition (Chernozhukov et al., 2013). This is the most appropriate technique to estimate how the total, and also the explained and unexplained gender wage gaps among Italian PhD holders, varies along the different quantiles of the wage distribution. This type of analysis is based on an inference on the counterfactual distribution method that makes it possible to evaluate the (possibly different) roles of both the covariates’ effect and the wage coefficients in the different parts of the distribution.

Following this methodology, the unconditional distribution of wages for men considered on their own, thus with both male characteristics and the wage function, is:

$$F_{Y[m,m]}(y) = \int F_{Y_m|X_m}(y|x)dF_{X_m}(x)$$

where $F_{Y_m|X_m}$ is the distribution of the male wages (Y_m) given male characteristics (X_m). Similarly, for women the unconditional distribution of wages will be:

$$F_{Y[f,f]}(y) = \int F_{Y_f|X_f}(y|x)dF_{X_f}(x)$$

where, once again, Y_f are female wages, and X_f female characteristics.

From these two equations we can derive the hypothetical counterfactual unconditional wage distribution for women with female characteristics, but with a male wage structure. This is the basic idea behind a gender wage gap, and exactly what we are trying to estimate. Thus, the hypothetical distribution that refers male wage returns on the entire distribution of wages will be $F_{Y[m,f]}$, and is equal to:

$$F_{Y[m,f]}(y) = \int F_{Y_m|X_m}(y|x)dF_{X_f}(x)$$

Following Chernozhukov et al. (2013), the conditional wage distribution may be estimated using the quantile regression originally proposed by Koenker and Bassett (1978). Thus, mirroring the Oaxaca-Blinder decomposition, it is possible to decompose the difference between unconditional wage distribution for the two genders. It should be noted that in these quantile decompositions a hundred different quantiles (and thus percentiles) are estimated, and standard errors are estimated using bootstrap techniques (with 100 replications).

4. Results

OLS estimates

Table 2 reports the results of the OLS estimation, where the log transformation of hourly wages is regressed on being a woman and the wide set of individual control variables described in section 3. Column 1 reports the results of the baseline specification, which includes individual, demographic and background controls. The estimated coefficients show that women earn on average 4.9% less than men per hour. When education-related controls are included, the estimated coefficient has a comparable magnitude, resulting in a wage gap of 4.4% (Column 2). In the third specification we exclude education-related controls and include the set of job-related controls, which leads us to drop 2,172 observations that are missing job-related variables, of which 1,116 are women (51%).⁷ The results, reported in Column 3, show that women earn on average 7.8% less than men. Finally, Column 4 reports the results of the most complete specification, which includes all the previous variables (individual, background, academic and job-related controls). In this estimation, being a woman is associated with an hourly wage that is 6.7% lower than that of men. All the coefficients are tightly estimated and statistically significant at the conventional value of 0.01%. The magnitude of our estimations is consistent with the ones provided for Italian university graduates by Piazzalunga (2018), whose results suggest the existence of a gender wage gap ranging from 6.3% to 7.2%.

Oaxaca-Blinder decomposition

The results for the Oaxaca-Blinder (O-B) decomposition analysis are reported in Table 3. As illustrated before, by using this technique the net hourly wage equation is estimated separately for men and women, and the raw gender difference is then split into two parts: one that is caused by the gender differences in

⁷ In order to provide a comparable analysis, we also run the first two regressions excluding the observations that present a missing value for the job-related variables. The estimation results, which are available upon request, show a negative and significant coefficient on the hourly wage for women, slightly lower than the previous estimations (3.8% and 3.0% respectively).

characteristics (i.e. the explained term), and a second that represents difference in returns (i.e. the unexplained term).

As in the previous table, the considered sets of control variables are progressively included in the analysis. Column 1 shows that women are paid less than men, with a raw difference in hourly wage amounting to 2.8%. The explained term shows a negative sign, meaning that if men had the same characteristics as women, they would have an even higher wage. In other words, women have greater endowments which are not paid for. Our results confirm that, *ceteris paribus*, women should have higher wages. What is more, the unexplained term shows that the gender gap cannot be fully explained by observable characteristics. Such evidence arises from all four of the specifications presented in Table 4, with the unexplained term showing increasing values as we include job-related controls. Indeed, in the complete model, the unexplained wage gap amounts to 6.7%.

Quantile decomposition

An interesting insight into the evolution of the gender wage gap is given by a decomposition analysis performed along the wage distribution of the sample. Figure 1 plots the total wage gap, the explained and the unexplained component at different points of the wage distribution. The raw gap remains between 0 and 5% up to the 80th percentile, when it shows a drop below zero before a steep increase right after the 90th percentile to more than 10%. Meanwhile, the explained gap is close to zero at the beginning of the distribution and shows a steadily decreasing trend, meaning that the higher the level of wages, the greater the disparity between women's endowments and what they are actually paid. In fact, the unexplained part of the gap increases steadily up to the 60th percentile. It then decreases between the 70th and 80th percentile, and finally soars to the very top of the distribution, showing that in Italy a "glass ceiling" effect also occurs for female PhD graduates at the beginning of their working careers.

5. Heterogeneity of the gap according to the scientific area of specialization and sector of employment

The results presented so far were achieved by analysing the entire sample of PhD holders included in the ISTAT survey. Nevertheless, there are reasons to believe that subsample analyses might also provide valuable insights for understanding the gender wage gap among PhD holders in Italy.

First, it is worth noting that in Italy, until recently, PhD studies were generally considered the first step of an academic career (Gaeta, 2013). Consistently with such a perspective, PhD holders, at least in the years immediately after graduation, are likely to look for a (frequently temporary) position in the university system. Since the Italian higher education system is built principally on public universities, and since public

universities are not supposed to carry out any form of discrimination, a gender wage gap should not be observed when looking at PhD graduates in academic jobs. For this reason, we estimate the O-B decomposition by splitting the sample into academic and non-academic jobs.

Second, the existing literature that focuses on university graduates suggests that gender wage gaps are highly heterogeneous across fields of study (Piazzalunga, 2018). This makes it prudent to check whether the scientific field of PhD specialization matters in the case of doctorate holders. This is achieved by estimating the O-B decomposition by splitting subsamples of respondents based on their field of expertise.

Table 4 reports the results calculated by sector of employment (academic and non-academic). For each subsample four models are presented, as in previous analyses. As expected, the raw difference between the hourly wage of men and women is smaller in the academic sector than in the non-academic sector. In the most complete specification for the academic sector (Column 4), the raw gap amounts to 1.7% and is not statistically different from zero. Instead, the same specification for those who work outside the academy (Column 8) results in a raw difference of 6.3%, which is statistically significant at the conventional level of 0.01%. However, in the academic sector gender discrimination is higher than in the non-academic sector. In fact, in the estimation of the full model for the academic sector (column 4), the unexplained difference amounts to 9%, while it amounts to 7.7% in the full model for the non-academic sector (column 8). Furthermore, the coefficient associated with explained characteristics is larger (in absolute terms) when estimating the O-B decomposition for the academic sector, while for the non-academic sector it is much smaller (in absolute terms), and is not statistically different from zero in three estimations out of four.

Table 5 reports the results of the O-B decomposition performed after splitting the sample according to the respondents' scientific areas of specialization. These results should be interpreted with care, as the number of observations can be small for some areas, which could lead to overestimation of the standard errors. Furthermore, women are remarkably underrepresented in some areas (e.g. 29% in Area 02 – Physics, 24% in Area 09 – Industrial and information engineering). The highest unexplained difference between hourly wages of men and women is observed in area 04 (Earth sciences), where the discrimination term amounts to 12.2%. A higher unexplained term than the one estimated on the full sample is observed in Area 03 – Chemistry (unexplained difference of 9.9%), Area 06 – Medicine (unexplained difference of 9.5%, and the highest raw gap observed, at 14.3%), and Area 13 – Economics and statistics (unexplained difference of 9.7%). In all areas except for Area 14 – Political and social sciences, the O-B decomposition results in a positive unexplained gap, although this is not always statistically significant, given the low number of observations. It is worth noting that in Area 14 – Political and social sciences, being a woman is associated with a negative unexplained difference (i.e. a wage premium), but the coefficient is not statistically significant at the conventional values.

6. Conclusion

Educational differences are considered one of the main causes of wage discrimination between men and women (Blau & Kahn, 2017). If women and men have unequal educational attainments, it is more likely that women suffer from discrimination and/or exclusion from the best paid jobs (Mussida & Picchio, 2014). Nevertheless, recent scholarly contributions have highlighted that in Italy the gender wage gap among college graduates has a similar magnitude to the one observed for the wider population (Piazzalunga, 2018). Such findings challenge the idea that one of the returns of a higher education is lower gender discrimination.

Within this context, our article contributes to the discussion by analysing the occurrence of a gender wage gap among the most educated population segment in Italy, i.e. PhD holders, at the beginning of their working careers.

The findings can be summarised as follows: gender discrimination exists (or rather, persists) even among Italian PhD holders, and it ranges between 4.9% and 6.7%, which is in line with the gender discrimination estimated for college graduates (5.6%) by Piazzalunga (2018). Most of the discrimination depends on different returns between men and women. In other words, at the same level of endowments women are paid less than men. All else being equal, women should have higher wages. Our estimations also highlight some differences between the academic and non-academic sectors: in the former, women and men have the same wages but women are discriminated against insofar as they are paid less for their endowments, while in the latter the lower wages that women receive compared to men are largely unexplained by observable factors. Finally, an analysis of the gender gap along the wage distribution shows that the raw gap and discrimination term increase steeply at the top of the distribution, providing evidence of a “glass ceiling” effect.

In conclusion, the evidence provided suggests that a negative relation between educational attainment and the gender wage gap cannot be taken for granted, at least in Italy. In fact, even women who have recently graduated at the highest level of education suffer from wage discrimination. Further research should tackle the issue of the gender wage gap for PhD holders in other countries, in order to shed more light on gender discrimination on returns from higher education.

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Tables and figures

Table 1: Descriptive statistics

Variable label	Obs	Mean	Std. Dev.	Min	Max	Mean for male subsample	Mean for female subsample
HWage	7,950	2.238	0.440	0.654	4.748	2.253	2.225
Sex	7,950	0.530	0.499	0	1	0	1
Classic	7,950	0.278	0.448	0	1	0.232	0.319
Scientific	7,950	0.499	0.500	0	1	0.523	0.477
Linguistic	7,950	0.024	0.154	0	1	0.007	0.040
Pedagogic	7,950	0.031	0.172	0	1	0.008	0.051
Technical	7,950	0.143	0.350	0	1	0.205	0.088
Professional	7,950	0.015	0.120	0	1	0.017	0.012
Artistic	7,950	0.003	0.051	0	1	0.002	0.003
Married	7,950	0.614	0.487	0	1	0.574	0.650
LivAlone	7,950	0.214	0.410	0	1	0.245	0.187
Children	7,950	0.365	0.481	0	1	0.327	0.399
North	7,950	0.387	0.487	0	1	0.383	0.391
South	7,950	0.368	0.482	0	1	0.380	0.357
ParentDegree	7,950	0.402	0.490	0	1	0.410	0.396
Orphan	7,950	0.002	0.042	0	1	0.002	0.002
DPA	7,950	0.902	0.297	0	1	0.907	0.898
PhDin2006	7,950	0.551	0.497	0	1	0.552	0.550
Area1	7,950	0.036	0.186	0	1	0.047	0.026
Area2	7,950	0.056	0.230	0	1	0.085	0.030
Area3	7,950	0.065	0.246	0	1	0.059	0.070
Area4	7,950	0.032	0.176	0	1	0.038	0.027
Area5	7,950	0.125	0.330	0	1	0.074	0.170
Area6	7,950	0.092	0.289	0	1	0.070	0.111
Area7	7,950	0.079	0.270	0	1	0.080	0.078
Area8	7,950	0.091	0.287	0	1	0.103	0.080
Area9	7,950	0.061	0.240	0	1	0.099	0.028
Area10	7,950	0.100	0.300	0	1	0.070	0.126
Area11	7,950	0.092	0.289	0	1	0.081	0.101
Area12	7,950	0.074	0.262	0	1	0.077	0.071
Area13	7,950	0.067	0.249	0	1	0.080	0.054
Area14	7,950	0.032	0.175	0	1	0.036	0.028
DegreeMagnaCumLaude	7,950	0.600	0.490	0	1	0.576	0.622
DegreeVote>105	7,950	0.837	0.369	0	1	0.820	0.853
DegreeGrade101-105	7,950	0.108	0.310	0	1	0.114	0.102
Visiting	7,950	0.300	0.458	0	1	0.319	0.283
Intime	7,950	0.899	0.301	0	1	0.892	0.905
Scholarship	7,950	0.781	0.414	0	1	0.782	0.780
Teaching	7,950	0.753	0.431	0	1	0.767	0.740
Age<30	7,950	0.288	0.453	0	1	0.282	0.293
Age=30	7,950	0.151	0.359	0	1	0.151	0.152
Age=31	7,950	0.138	0.345	0	1	0.135	0.142
Age>32	7,950	0.313	0.464	0	1	0.326	0.302
Tenure	5,778	2.959	1.483	1	6	2.981	2.941
Services	7,950	0.908	0.289	0	1	0.895	0.919
Industry	7,950	0.076	0.266	0	1	0.088	0.066
Migration	7,950	0.242	0.429	0	1	0.264	0.223
Fulltime	7,950	0.614	0.487	0	1	0.695	0.543
PIVA	7,950	0.117	0.321	0	1	0.136	0.100

Table 2: OLS results

	(1)	(2)	(3)	(4)
	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage
Female	-0.0489*** (-4.85)	-0.0437*** (-4.25)	-0.0778*** (-7.41)	-0.0668*** (-6.20)
Observations	7,950	7,950	5,778	5,778
Background	X	X	X	X
Demographic	X	X	X	X
Education		X		X
Job quality			X	X

Note: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Background controls are: 2006 cohort, parents with degree, no living parents, parents in the public sector, high school. Demographic controls are: married, living alone, having a child, macro-area. Education controls are: master vote, scientific area of PhD, scholarship, visiting abroad, taught during studies, PhD completed in time.

Table 3: Oaxaca-Blinder decomposition results

	(1)	(2)	(3)	(4)
	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage
Men	2.253 ^{***} (313.38)	2.253 ^{***} (313.38)	2.232 ^{***} (268.55)	2.232 ^{***} (268.54)
Women	2.225 ^{***} (328.16)	2.225 ^{***} (328.16)	2.211 ^{***} (285.77)	2.211 ^{***} (285.77)
Difference	0.0281 ^{***} (2.84)	0.0281 ^{***} (2.84)	0.0211 [*] (1.86)	0.0211 [*] (1.86)
Explained	-0.0208 ^{***} (-6.47)	-0.0156 ^{***} (-3.52)	-0.0566 ^{***} (-9.13)	-0.0456 ^{***} (-6.53)
Unexplained	0.0489 ^{***} (4.85)	0.0437 ^{***} (4.26)	0.0778 ^{***} (7.43)	0.0668 ^{***} (6.23)
Observations	7,950	7,950	5,778	5,778
Background	X	X	X	X
Demographic	X	X	X	X
Education		X		X
Job quality			X	X

Note: t statistics in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. Background controls are: 2006 cohort, parents with degree, no living parents, parents in the public sector, high school. Demographic controls are: married, living alone, having a child, macro-area. Education controls are: master vote, scientific area of PhD, scholarship, visiting abroad, taught during studies, PhD completed in time.

Table 4: Oaxaca-Blinder decomposition results by type of job

	<i>Academy</i>				<i>Non-academy</i>			
	(1) Log.Hour wage	(2) Log.Hour wage	(3) Log.Hour wage	(4) Log.Hour wage	(5) Log.Hour wage	(6) Log.Hour wage	(7) Log.Hour wage	(8) Log.Hour wage
Men	2.350*** (246.43)	2.350*** (246.43)	2.332*** (198.65)	2.332*** (198.65)	2.118*** (212.39)	2.118*** (212.39)	2.122*** (193.75)	2.122*** (193.75)
Women	2.321*** (265.12)	2.321*** (265.12)	2.314*** (224.50)	2.314*** (224.50)	2.068*** (218.69)	2.068*** (218.69)	2.059*** (201.14)	2.059*** (201.14)
Difference	0.0298** (2.31)	0.0298** (2.31)	0.0171 (1.10)	0.0171 (1.10)	0.0500*** (3.64)	0.0500*** (3.64)	0.0633*** (4.22)	0.0633*** (4.22)
Explained	-0.0258*** (-5.96)	-0.0221*** (-4.59)	-0.0766*** (-9.18)	-0.0734*** (-8.60)	-0.00531 (-1.21)	-0.00564 (-1.21)	-0.0123 (-1.49)	-0.0139* (-1.67)
Unexplained	0.0556*** (4.24)	0.0520*** (3.99)	0.0937*** (6.36)	0.0905*** (6.17)	0.0554*** (3.92)	0.0557*** (3.95)	0.0756*** (5.48)	0.0772*** (5.62)
Observations	4,796	4,796	3,246	3,246	3,154	3,154	2,532	2,532
Background	X	X	X	X	X	X	X	X
Demographic	X	X	X	X	X	X	X	X
Education		X		X		X		X
Job quality			X	X			X	X

Note: t statistics in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. Background controls are: 2006 cohort, parents with degree, no living parents, parents in the public sector, high school. Demographic controls are: married, living alone, having a child, macro-area. Education controls are: master vote, scientific area of PhD, scholarship, visiting abroad, taught during studies, PhD completed in time.

Table 5: Oaxaca-Blinder decomposition by academic area

Area:	01	02	03	04	05	06	07	08	09	10	11	12	13	14
	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage	Log.Hour wage
Men	2.212*** (71.45)	2.279*** (99.54)	2.173*** (99.46)	2.208*** (53.7)	2.138*** (80.26)	2.471*** (73.17)	2.138*** (85)	2.174*** (74.16)	2.243*** (94.31)	2.324*** (54.39)	2.226*** (71.53)	2.252*** (62.4)	2.275*** (70.99)	2.111*** (55.12)
Women	2.178*** (50.45)	2.302*** (62.36)	2.141*** (98.45)	2.207*** (47.77)	2.153*** (135.25)	2.328*** (92.58)	2.170*** (77.77)	2.222*** (70.79)	2.188*** (55.03)	2.279*** (85.95)	2.201*** (94.26)	2.196*** (65.68)	2.199*** (72.15)	2.218*** (44.55)
Difference	0.034 (0.64)	-0.0227 (-0.52)	0.0318 (1.03)	0.000752 (0.01)	-0.0149 (-0.48)	0.143*** (3.40)	-0.0317 (-0.84)	-0.0475 (-1.11)	0.0544 (1.17)	0.0457 (0.91)	0.0249 (0.64)	0.0552 (1.12)	0.0768* (1.74)	-0.107* (-1.70)
Explained	-0.00197 (-0.05)	-0.0337 (-1.12)	-0.0674*** (-3.06)	-0.121** (-2.38)	-0.0470** (-2.57)	0.0483 (1.61)	-0.103*** (-3.71)	-0.0980*** (-3.21)	-0.0137 (-0.48)	-0.00619 (-0.19)	-0.0266 (-1.05)	-0.0221 (-0.79)	-0.0208 (-0.79)	-0.0709 (-1.54)
Unexplained	0.0359 (0.82)	0.011 (0.31)	0.0992*** (-3.35)	0.122** (2.03)	0.0322 (1.15)	0.0951*** (2.59)	0.0709** (1.96)	0.0505 (1.1)	0.0681* (1.69)	0.0519 (1.27)	0.0515 (1.49)	0.0773 (1.58)	0.0976** (2.32)	-0.0362 (-0.61)
Observations	228	375	422	200	813	465	464	431	362	562	516	363	394	183

Note: t statistics in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. Controlling for individual background, demographic controls, quality of education and job quality. Areas are: 01 – Mathematics and informatics; 02 – Physics; 03 – Chemistry; 04 – Earth sciences; 05 – Biology; 06 – Medicine; 07 – Agricultural and veterinary sciences; 08 – Civil engineering and architecture; 09 – Industrial and information engineering; 10 – Antiquities, philology, literary studies, art history; 11 – History, philosophy, pedagogy and psychology; 12 – Law; 13 – Economics and statistics; 14 – Political and social sciences.

Figure 1: Differences in wages between men and women; analysis at different points of the wage distributions. Estimated by means of a quantile decomposition controlling for individual background, demographic controls, quality of education and job quality.

