



Research Article

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The Gender Wage Gap among Ph.D. Holders: Evidence from Italy

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Abstract: This paper contributes to the literature on the gender wage gap by empirically analyzing those workers who hold the highest possible educational qualification, i.e., a Ph.D. The analysis relies on recent Italian cross-sectional data collected through a survey on the employment conditions of Ph.D. holders. The Oaxaca–Blinder decomposition analysis and quantile decomposition analysis are carried out, and the selection of Ph.D. holders into employment and STEM/non-STEM fields of specialization is taken into account. Findings suggest that a gender gap in hourly wages exists among Ph.D. holders, with sizeable differences by sector of employment and field of specialization.

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

JEL codes: J31, J71

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1 Introduction

Although much progress has been made in reducing gender inequality, the issue remains crucial for contemporary societies and continues to occupy a prominent place in the political agenda of many national governments. This is also valid for the European Union (EU), which considers equality between women and men to be a fundamental right and an essential feature of stable democracies (European Commission 2018), and has therefore put much effort into the elaboration of strategies devoted to fostering it (European Commission 2020; European Union 2015). Not surprisingly, some of these strategies focus on fighting economic gender inequality and, more specifically, inequality of wages, which is recognized as a moral and socio-economic issue *per se*.

Scholars have devoted considerable attention to studying the incidence and determinants of the gender wage gap (GWG) (for an extensive review of previous studies, see Bishu and Alkadry 2017). According to human capital theory, the GWG arises because of gender differences in qualifications. These differences, in turn, are connected to factors such as the gender gap in investment in education (Becker 1985), women's preference for less career-oriented fields of study and occupation (Bobbitt-Zeher 2007), and the impact of family duties on women's accumulation of work experience (Becker 1985; Mincer and Polachek 1974). Nevertheless, scholars have also demonstrated that unexplained gender differences in wages sometimes persist even when controlling for qualifications and work experience. As long as there is no other unobserved variable driving such a result, this would reveal the possible existence of systematic gender discrimination in the labor market (Blau and Kahn 2017).

One valuable way to reduce the risk of unobserved variables bias in investigating such discrimination is to restrict the analysis to a homogeneous group of workers who theoretically share similar characteristics, at least in terms of education acquired. By relying on this strategy, recent studies have demonstrated that in European countries the GWG also exists among people with the same level of education, although it is lower among the more highly educated (de la Rica et al. 2008; Garcia-Prieto and Gómez-Costilla 2017; Mussida and Picchio 2014).

This paper contributes to the existing literature by proposing an empirical analysis of the GWG among Ph.D. holders. On the one hand, this means focusing on a relatively homogeneous sample of workers and therefore implies limiting the risk of unobservable factors other than discrimination that might explain any observed wage differential. On the other hand, this allows us to check whether a GWG is observed when the analysis is restricted to those who hold the highest existing educational qualification, which might provide useful information for assessing the impact of educational level on the GWG.

To the best of our knowledge, the issue of the GWG among Ph.D. holders has been explicitly addressed by a limited number of papers. Webber and Canché (2015) find a significant GWG among Ph.D. recipients in Science and Engineering in the United States. Schulze (2015) finds that the GWG among Ph.D. holders in the UK is high among those employed in non-academic sectors, while low, albeit still present, among those who are employed as academics.

Our paper enriches this limited literature by analyzing data from Italy, which is an interesting case study for two reasons. First, recent empirical contributions focusing on this country have found a sizeable GWG among university graduates, albeit with marked differences between fields of study (Piazzalunga 2018). This calls for a detailed inspection of the case of Ph.D. holders, to determine whether the gap varies according to the level of education. Second, studies suggest that in Italy the Ph.D. holders' economic potential is not fully exploited; indeed, doctorate holders frequently report over-education and job dissatisfaction (Ermini, Papi, and Scaturro 2017; Gaeta, Lavadera, and Pastore 2017; Garcia-Prieto and Gómez-Costilla 2017; Parenti, Pinto, and Sarno 2020). From this perspective, it makes sense to investigate whether the picture is also exacerbated by any gender wage gap that might be at the origin of different levels of satisfaction.

Our analysis employs cross-sectional data collected by the Italian National Institute of Statistics (ISTAT) through a survey of Ph.D. holders who completed their studies in 2004 and 2006 and were interviewed a few years after graduation. These data allows us to analyze the GWG by considering both Ph.D. holders still working in the academic sector and those who have experienced intersectoral mobility (i.e., a shift towards the non-academic market). The analysis of recent graduates is valuable because it allows us to focus on wage differentials that are not affected by large gaps in working experience. The empirical investigation we propose relies on (i) Oaxaca–Blinder (OB) decomposition; (ii) OB analyses that take into account selection into employment and selection into a Ph.D. field of study; (iii) quantile decomposition analyses.

Our findings suggest that in Italy a sizable GWG exists among Ph.D. holders. The raw wage difference between men and women is larger inside the academia, where it is partially explained by job-related variables, while the smaller raw wage differential outside the academia remains completely unexplained. Those doctoral graduates who are specialized in non-STEM areas face higher levels of discrimination outside than inside the academia, while the opposite is true (albeit a smaller difference) for those specialized in STEM areas. Moreover, the analysis of wages along the distribution suggests some evidence of a “ceiling effect”.

The paper is organized as follows. Section two provides a brief review of the most relevant literature. To give some information about the context of our

analysis, section three describes the main features of doctoral education in Italy and presents some data and previous contributions that studied Ph.D. holders' occupational outcomes in this country. Section four illustrates the data used in the present study and the econometric approach adopted to investigate the GWG. Section five presents and discusses our results by paying attention to the heterogeneity of our findings according to Ph.D. holders' scientific area of specialization and sector of employment. Finally, section six concludes.

2 The Literature on the Gender Wage Gap

Research on the extent and drivers of the GWG (Alkadry and Tower 2006; Miller 2009; Xiu and Gunderson 2014) is one of the richest branches of literature on gender inequality in the labor market. The success of this topic is due to two main reasons. First, the gap in earnings represents per se an essential measure of gender inequality in the labor market; second, inspecting the reasons behind gender disparities in economic rewards allows us to highlight the existence of other specific types of discrimination in the workplace. Detailed meta-analyses of previous contributions on the GWG (Bishu and Alkadry 2017; Jarrell and Stanley 2004; Stanley and Jarrell 1998; Weichselbaumer and Winter-Ebmer 2005) suggest that the GWG is associated with a disparity in access to hiring and promotions (Arulampalam, Booth, and Bryan 2007; Baxter and Wright 2000; Bjerk 2008; Gobillon, Meurs, and Roux 2015), a disparity in access to workplace authority (Alkadry and Tower 2011; Bygren & Galher 2012; Elliott and Smith 2004; Jacobs 1992), and institutional gender representation (Adams and Funk 2012; Budig 2002; Dixon and Seron 1995).

The link between the GWG and other forms of gender discrimination in the labor market can be traced back to the human capital theory (Becker 1964). According to this approach, the GWG depends on discrimination, i.e., different returns guaranteed for workers with equal productivity (Becker 1964) or gender differences in human capital endowment. Following this intuition, scholars have devoted considerable attention to investigating factors explaining such different individual endowments, paying particular attention to gender disparities in educational attainment and the analysis of related occupational and sectoral segregation.

Following Katz and Murphy (1992), who pointed out the importance of education in occupational opportunities and related earning capacities, several scholars have focused on the relation between the GWG and education (Blau and Kahn 2008; de la Rica et al. 2008; Kolesnikova and Liu 2011). The literature has identified two mechanisms by which education affects occupational choices and,

consequently, the wages associated with them: (i) vertical segregation, i.e., concentration in lower levels of education and less prestigious institutions; and (ii) horizontal segregation, i.e., engagement in certain fields of study (Charles and Bradley 2002; Charles and Grusky 2004).

The literature has extensively addressed segregation by fields of study (i.e., horizontal segregation), its historical trends, and sizeable incidence and effects (Alfano, Gaeta, and Pinto 2021; Charles and Bradley 2009), leading some scholars to consider it a “stubborn basis of inequality” (Davies and Guppy 1997: p. 1421).

The idea at the beginning of the current century that a trend of desegregation was underway, albeit slowly (Ramirez and Wotipka 2001), has been partially disputed by scholars observing persistence of the phenomenon over time and the invariance across countries of horizontal gender segregation in higher education (Barone 2011). There is a broad consensus around the idea that women are underrepresented in STEM and ICT, and are instead concentrated in humanistic fields (Brush 1991; Seymour 1995), more specifically in nursing and education (Jacobs 1995). Nevertheless, significant differences regarding empirical approaches and findings have emerged in the research of explanations for this phenomenon (Becker 1985; Charles and Bradley 2002; Clark 1992; Maple and Stage 1991; Polachek 1978; Strenta et al. 1994; Ware and Lee 1988; Wilson and Boldizar 1990).

Although the dynamics of horizontal segregation in education impact on equality in the labor market in several ways, it is worth noting that they directly impact on occupational segregation (Bradley 2000; Charles 2005; Frehill 1997; Polachek 1981), and consequently on the size of the wage gap by excluding women from the best-paid jobs (Bobbitt-Zeher 2007; Davies and Guppy 1997; European Commission 2005). Scholars have also observed how this phenomenon negatively affects economic growth (Barro and Lee 1994; Klasen 2002).

Despite this vast literature on segregation by field of study, researchers have partially ignored vertical segregation. That is probably because, since the beginning of the 1980s, the share of women among bachelor’s graduates in the USA and most industrialized countries has surpassed men (Jacobs 1996). Recent figures suggest that, on average, women represent the majority of enrolled and graduated students for bachelor and master’s courses in OECD countries (Flabbi 2012). This finding suggests that, at least from a quantitative perspective, access to higher education is not a significant feature of gender segregation. This shift is considered to be a function of a certain number of social and cultural issues on the one side (Ramirez and Boli 1982; Solomon 1985) and the structure of the labor market and educational systems on the other (Graham 1978; Walters 1986).

Some critical issues regarding the role of education in mediating the GWG require significant attention. First, education is considered an essential tool for

reducing gender inequality (Montgomery and Powell 2003). Still, controversial results have been provided on the size of the wage gap at higher levels of education and on the variability of the gap at different educational levels (Gill and Leigh 2000; Wood, Corcoran, and Courant 1993). Second, the observed feminization of tertiary education has not been accompanied by gender desegregation (Bobbitt-Zeher 2007; Jacobs 1996).

Weinberger (1998) analyses data from a survey of recent college graduates in the USA one or two years after achieving the degree (1983 and 1984), and finds a 9% wage gap among white women and 16% among black women with respect to white men. Results in the USA are even lower in Fuller and Schoenberger (1991), who found a gap of 7%, and in Bertrand and Hallock (2001), who found a gap of at least 45% among the top managerial jobs in the USA between 1992 and 1997, of which the unexplained component was just 5%.

Different results are reported in recent work by Behr and Theune (2018), who look at the German case. The authors analyze survey data (2001) on wages related to young workers' first job after graduation and find a sizable average hourly pay gap at labor market entry (25%), with significant differences across the income distribution. In line with Kunze's (2003) results, such a gap is very similar to those observed for the overall population.

De la Rica et al. (2008) provide a study of the wage gap in Spain by exploring panel data concerning workers employed full-time aged 16–64 years in 1999 and 1994–2001. They find that the average gap is higher for highly educated workers and increases along with the wage distribution (“glass ceiling”). At the same time, it decreases for workers with lower levels of education.

Looking at contributions focused on Italy, Addabbo and Favaro (2011) have observed a significant impact of educational attainment on the wage gap. Detecting a sizable wage loss (ranging between 4.8 and 11.3%, of which the unexplained component ranges between 8 and 14%), their study reveals that, for any level of wage, highly educated women experience a lower wage gap than less-educated women. Moreover, they detected the existence of a “glass ceiling” effect only for the first group. Another impressive contribution is that of Mussida and Picchio (2014). Their analyses control for selection into the workforce and confirm previous findings regarding the importance of educational attainment by revealing that less-educated women experience a more substantial wage penalty. Moreover, they provide some evidence of a “sticky floor” among less-educated women.¹

¹ Unlike most common definitions used in the literature, both studies (Addabbo and Favaro 2011; Mussida and Picchio 2014) define the “highly educated” as workers with at least a post-compulsory school diploma (3–7 level according to the ISCED (International Standard Classification of Education)).

A more recent contribution by Piazzalunga (2018) analyzed a sample of Italian university graduates four years after completion of their degree. It observes an under-representation of women in fields of study offering the highest wage prospects (such as maths-sciences and engineering). It provides evidence of a large GWG among graduates who completed their studies in the following fields: Law, Political Science, Social Sciences, and Economics-Statistics (Piazzalunga 2018). This study also provides some evidence of a “glass ceiling” effect. The gap estimated by the author when looking at recent graduates (5.6%) is similar to that calculated by Eurostat in 2011 when looking at the wider population (Piazzalunga 2018).

Narrowing the focus to Ph.D. workers, to the best of our knowledge, only a limited number of studies focus specifically on the GWG. Webber and Canché (2015) provide a longitudinal analysis of wages earned by approximately 10,000 US Ph.D. recipients in Science and Engineering who were tracked over 10 years. Their findings show that women earn average yearly salaries that are \$10,000 lower than their male peers, regardless of the sector of employment chosen after Ph.D. completion, and that growth in pay associated with years elapsed since Ph.D. completion is lower for female holders. By using data collected six months and 42 months after graduation, Schulze (2015) studies the case of UK Ph.D. holders who completed their degree in 2004–05. After controlling for a comprehensive set of potential drivers, she finds that a remarkable GWG (i.e., an unexplained gap) exists among those employed in the non-academic sectors (approximately –22 log points) and that this remains stable over time. Meanwhile, employment within the academic sector turns out to be less affected by the wage gap (approximately –3 log points, which turn out not to be statistically significant).

3 The Italian Doctoral Education and Career Prospects of Ph.D. Holders

Doctoral education was introduced in Italy in 1980² with the creation of a somewhat centralized organization. The law stated that Ph.D. courses could be offered only by universities authorized by the Italian Ministry of Education, which also determined the number of available Ph.D. courses; furthermore, while Ph.D. students were locally selected, their final evaluation was carried out by field-specific national boards of examiners. Until the end of the 1990s, a doctoral education was mainly interpreted as the first step of an academic career, and Ph.D. students were

2 Decree of the President of the Republic n. 382/1980.

low in number; Argentin, Ballarino, and Colombo (2014) show that the number of new Ph.D. holders per year was approximately 2000 in the mid-1980s, and lower than 4000 at the end of the 1990s.

At the end of the twentieth century, a few national policy interventions – linked to the reform and harmonization of higher education systems in the EU – significantly modified this organizational framework. On the one hand, they increased universities' autonomy in establishing doctoral courses, defining course content, and selecting and examining candidates³. After the adoption of these policies, the number of new Ph.D. candidates and holders rose dramatically. Argentin, Ballarino, and Colombo (2014) show that in 2008 the annual number of new Ph.D. holders reached 12,000. This made it *de facto* impossible for all these Ph.D. holders to find a job in the academic sector.

At the beginning of 2010, new national policy interventions⁴ introduced strict requirements for the accreditation of university doctoral courses by the Italian Ministry of Education.⁵ As a consequence, courses were slightly reduced in number. While precise figures on the annual number of new Ph.D. holders are not available, recent estimates reveal that between 2008 and 2014, the number of open Ph.D. positions decreased by approximately 20% (ADI 2014).

On the other hand, the policy interventions carried out from the late 1990s stressed the role of Ph.D. education as third-cycle studies that could provide skills and competencies that were potentially valuable in non-academic employment.⁶ In line with this perspective, recent data reveal that universities are no longer the only employment destination of Ph.D. holders who complete their studies in Italy. Data from the “Survey on the employability of Ph.D. holders” (“*Indagine sull’inserimento professionale dei Dottori di Ricerca*”) carried out by the Italian National Institute of Statistics in 2010 reveal that a few years after graduation, about 36% of Ph.D. holders are still employed in the academic sector, while the remainder works outside universities. Unfortunately, studies on the occupational outcomes of Ph.D. holders reveal that while unemployment is low compared with university graduates, overeducation and overskilling are widespread among those

3 Italian national ministerial decree 509/1999.

4 Principally law 240/2010 and Ministerial Decree 45/2013.

5 The most important requirements concerned: a) the size and composition of the teaching board, which had to include at least sixteen members, of whom no more than one fourth were Assistant Professors. They all had to specialize in scientific sectors consistent with the objective of the Ph.D. course; b) the scientific qualification of the teaching board, measured by examining the quality of the scientific publications of its members; c) the existence of adequate structures; d) the existence of specific training activities available for Ph.D. students.

6 Berlin Communication 2003; Italian national law 3 July 1998, n. 210, art. 4; Italian national decree 8 February 2013, n. 45, art. 1.

working in non-academic sectors (Gaeta 2015). In addition, they also provide some evidence that among Ph.D. holders, women have a slightly lower probability of being employed than men (Gaeta 2015).

4 Data

Our data source is the first edition of the Italian “Survey on the employability of Ph.D. holders” (*“Indagine sull’inserimento professionale dei Dottori di Ricerca”*) carried out by ISTAT between December 2009 and February 2010. This survey observes the early stage career outcomes reported by doctoral graduates who completed their Ph.D. in Italy in 2004 and 2006 and were interviewed 5 and 3 years after graduation. The analysis is based on the publicly available dataset that collects the information gathered through this survey.

The survey involved a population made up by two cohorts of doctoral graduates who completed their studies in 2004 and 2006 (8433 and 10,125 graduates, respectively). The response rate reported by the survey is approximately 70%, which resulted in 12,964 completed interviews (ISTAT 2013a). The publicly available data provided by ISTAT⁷ include 8814 observations resulting from sampling the original survey data, which was carried out to avoid privacy problems (ISTAT 2013b). Among these 8814 observations, 3928 refer to Ph.D. holders who graduated in 2004, while 4886 refer to those from the 2006 cohort. Our analyses are based on this sample. Of course, the self-selection of respondents into the survey generates the risk of non-sampling errors, which must be kept in mind when considering our results.

The ISTAT survey includes a comprehensive set of valuable data for our analysis insofar as it identifies the wage of respondents and individual-level features that might influence it.

The variable we are principally interested in is the log of the net hourly wage. The ISTAT data records the net monthly salary self-declared by respondents (*monthly wage*). The average net monthly salary in the sample under scrutiny is approximately €1456.00 among respondents employed in universities and €1655.00 among those employed in non-academic activities. In addition, the survey also reports the number of hours respondents declare they devote to work each week (*weekly hours*). We used this information to estimate the log of hourly wages by taking the natural logarithm of the monthly wage multiplied

⁷ See the following webpage (in Italian) on the official ISTAT website <https://www.istat.it/it/archivio/87536> [last access on 24/9/2020].

by 12 and divided by the number of hours worked per week multiplied by 52. In formal terms:

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

Some of the interviewed Ph.D. holders did not reply to the survey question concerning their earnings. More specifically, 864 observations (approximately 10% of the total sample) report a missing value for the variable that records wages. For most of them (about 71%), the reason is unemployment. After excluding these observations, our dataset is made up of 7950 individuals.

Following the literature on Ph.D. holders' wage determinants (Gaeta, Lavadera, and Pastore 2017), our analysis extracted from the ISTAT survey data those variables that observe micro-level features that are presumed to exert some impact on respondents' salary. Given the objective of the study, the dichotomous gender variable is, of course, the most interesting one.

Alongside the gender variable, the other considered covariates might be grouped as follows. All the covariates are categorical variables with the exception of *experience*. Details and descriptive statistics are available in Annex 1.

The first set allows us to observe the respondents' background by controlling for family educational background, the employment status of the respondents' parents, and the secondary education diploma.

The second set of variables includes socio-demographic characteristics, capturing marital, cohabitation, and offspring status. Moreover, it contains data about a respondent's age and the geographical area of Italy in which he or she lives to capture the significant heterogeneity of these areas in terms of economic development (Ercolano 2012).

The third set of covariates controls for features of the respondents' educational background, allowing us to observe respondents' final grade at the end of their master's degree. In addition, we observe Ph.D.-related features by identifying the scientific area in which respondents completed their Ph.D.;⁸ whether one benefitted from a scholarship during their Ph.D, spent time abroad as part of their Ph.D., taught lessons during their Ph.D. and completed the Ph.D. within the standard deadline, i.e., within three years. Finally, we control for the 2006 (2004) cohort.

8 Areas are: 01 – Mathematics and Information sciences; 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.

The fourth set of covariates includes job-related variables, allowing us to identify whether the interviewee holds a job in the public sector or works in academia, whether the respondent is self-employed, and whether she/he has a fixed-term contract. Since migration is triggered by one's willingness to obtain better opportunities (e.g., higher wages), we also control for working in an Italian region different from the one where they completed their Ph.D. studies. Finally, we control for job positions by merging non-academic (*non-skilled jobs, qualified profession, technical profession, administrative and managerial profession, specialist in mathematics, specialist in engineering, specialist in life science, specialists in health, specialist in human sciences, specialist in research and teaching*), and academic job positions (*Professor, teaching professor, researcher, contract researcher, language assistant, research assistant, graduated technician, research fellow, post-doc grant holder, research grant holder*).⁹ We let the academic job position prevail for the 1881 observations (23.7% of the sample) that expressed both non-academic and academic job positions. Nevertheless, we also perform the analysis on the two separate variables. The results, which are available upon request, do not change meaningfully (except for the sample size) from those provided in the next section.

One additional variable measures respondents' years of employment in the job they hold when interviewed. Unfortunately, it is worth noting that this variable reports a high number of missing values (2891, 32.8% of the sample). Thus, the analyses using these variables report a lower number of observations, and their results should be taken with caution.

A final set of covariates observes respondents' vertical job/education mismatch, which has been proven to be crucial in determining wages (Gaeta, Lavadera, and Pastore 2017). Following the existing literature, we include a variable for overeducation, i.e., holding a job for which the Ph.D. title was neither required nor useful, and a variable measuring overskilling, i.e., having a job that is carried out without using skills acquired through doctoral studies. Both these variables are included in the original ISTAT dataset and based on respondents' self-assessment.

Descriptive statistics in Annex 1 offer interesting initial insights. Contrary to the figures about the population of Ph.D. holders calculated in other countries

⁹ These are the categories identified by ISTAT for the survey whose correspondent Italian nomenclature is: *Professore Ordinario or Associato di ruolo (a tempo indeterminato), Professore a contratto, Ricercatore di ruolo a tempo indeterminato, Ricercatore a contratto, Collaboratore ed Esperto linguistico, Titolare di contratto per attività di ricerca, Tecnico laureato, Assegnista di ricerca, Titolare di borsa post-dottorato, Titolare di borsa di studio/ricerca*.

(Schulze 2015), in our case, women represent the majority of the sample scrutinized (54%).¹⁰ The age of respondents does not show significant differences by gender: 29% of women and 28% of men are younger than 30.

Contrary to evidence in other countries (Webber and Canche 2015), our sample does not show segregation in the STEM¹¹ sector. The percentage of women graduates in STEM (53%) is similar to women's representation in the entire sample (54%). Looking at gender distribution by field of study, women are highly concentrated in Biology, Antiquities (Philology-Literary Studies-Art History), and Medicine. Also, in Chemistry, Agricultural-Veterinary Sciences, and History (Philosophy–Pedagogy–Psychology), there is a high presence of women. The lowest presence is observed in Industrial and Information Engineering (24%) and Physics (28.5%), followed by Mathematics and Information Sciences (38%), Economics and Statistics (44%), Earth Sciences (45%), and Political and Social Sciences (48%).

The unemployment rate in the sample is low (7.5%), although women are overrepresented among the unemployed (65%). The number of Ph.D. holders employed in an academic job is low (35%) but, surprisingly, women and men are relatively equally represented (50.3 and 49.7%, respectively). Nevertheless, gender representation among academic positions is unequal, as women are underrepresented among professors (35%), researchers (43%), and post-doc researchers (44%), while they are overrepresented among teaching professors (56%), language assistants (73%), research assistants (56%), graduated technicians (61%) and research fellows (57%). It should be noted that, overall, men hold most of the managerial and administrative positions (61%), while women are the majority among non-skilled professions (60%).

5 Methodology

To assess the GWG, we apply the Oaxaca–Blinder decomposition. This technique was initially developed in labor economics and has since been used widely to analyze the determinants of male/female earnings differentials as a means to

10 It is worth noting that, although we have no detailed data for non-respondents, ISTAT published percentages of respondents to the survey. The percentage is higher among women in both 2009 and 2010 (ISTAT 2013a).

11 STEM areas are: Mathematics and Information Sciences; Physics; Chemistry; Earth Sciences; Biology; Medicine; Agricultural and Veterinary Sciences; Civil Engineering and Architecture; Industrial and Information Engineering. Non-STEM areas are: Antiquities, Philology, Literary Studies, Art History; History, Philosophy, Pedagogy and Psychology; Law; Economics and Statistics; Political and Social Sciences.

estimate the level of discrimination in the labor 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 feature giving different returns (unexplained variation).

The idea is to decompose the log of hourly wages 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 character across groups (the so-called unexplained component). The general model is:

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

where $g = \{m, f\}$, X_g is the vector of all the explanatory variables, β_g is the vector of the coefficients, and ε_g is the error. However, we estimate the above separately for a female (f) set and a pooled set (p) that also includes males (m) (please notice that the gender dummy is included in the pooled equation). In our notation, the O–B decomposition is thus:

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

The first term $(X_m - X_f)$ corresponds to the difference in performance between the male and female (points gap) due to the differences in the characteristics of each group. β_p is the estimated non-discriminatory wage structure of the pooled sample, following Neumark (1988). On the other hand, the second term corresponds to the unexplained component, i.e., the differences in returns due to all the unobserved variables. In this family of models, which are principally applied in labor economics, the second term is often labeled “discrimination”, since it provides a measure of the difference in wages that cannot be explained by clear differences in the characteristics of the two groups. In other words, this is the relative difference in wages that can be attributed to unobserved traits; or, in a broader interpretation: everything that is not related to observable characteristics.

While the O–B strategy allows us to address different endowments among groups, it does nothing for the potential bias of self-selection. The differential in wages can be due to non-random selection at various stages, be it in employment, sector of Ph.D., or academic job. For this reason, we perform a second set of analyses enhancing the O–B decomposition by estimating the women equation in (2) via a two-step Heckman correction, following the approach suggested by Jann (2008). Therefore, we estimate a first-stage equation where the probability of selection depends on individual variables. We then include the predicted individual probabilities in the decomposition equation and adjust the O–B estimation accordingly.

The third econometric approach employed here is quantile decomposition (Chernozhukov, Fernández-Val, and Melly 2013). This is the most appropriate

technique to estimate how the total and the explained and unexplained gender wage gaps among Italian Ph.D. holders vary along the different quantiles of the wage distribution. This type of analysis is based on 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 other 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:

$$F_{Y_{[m,m]}}(y) = \int F_{Y_m|X_m}(y|x)dF_{X_m}(x) \quad (3)$$

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:

$$F_{Y_{[f,f]}}(y) = \int F_{Y_f|X_f}(y|x)dF_{X_f}(x) \quad (4)$$

where, once again, Y_f are female wages and X_f are 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 the gender wage gap, and precisely what we are trying to estimate. Thus, the hypothetical distribution that refers to male wage returns on the entire distribution of wages will be $F_{Y_{[m,f]}}$, which is equal to:

$$F_{Y_{[m,f]}}(y) = \int F_{Y_m|X_m}(y|x)dF_{X_f}(x) \quad (5)$$

Following Chernozhukov, Fernández-Val, and Melly (2013), the conditional wage distribution may be estimated using the quantile regression proposed initially 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 1000 replications).

These techniques are widely applied in the most recent empirical research on the wage gap. Nevertheless, one must keep in mind that their application might be biased by endogeneity, and our analysis should therefore be considered the search for robust *ceteris paribus* correlations.

6 Results

6.1 O–B Decomposition

Table 1 reports the O–B decompositions performed on the full sample by progressively adding the controls' groups. Column (1) reports the results of a specification that only includes background and demographic variables; the results in Column (2) take into account the education-related controls; Column (3) reports a model that also includes job-related variables; in Column (4) vertical mismatch is accounted for. Finally, Column (5) reports the results calculated through the complete specification, including years of working experience among the covariates. The table displays the estimated log of hourly wages for men and women and the raw wage difference between them, which is decomposed in its explained and unexplained parts. Full results, including sign, magnitude, and statistical significance of all the control variables, are not reported for the sake of space but are available upon request to the authors.

Looking at the table, the first result that stands out is the size and statistical significance of the wage difference, i.e., the raw gap between men and women. Compared to that detected among college graduates (5.6%) by Piazzalunga (2018), it appears to be significantly lower: 2.8% in the first and second specifications, which only consider socio-demographic and educational controls. As an effect of the inclusion of new variables and/or to the change in sample size due to missing data, the raw gap is reduced to 2.4% (in the third and fourth specifications) and 1.7% (in the last specification). However, the latter coefficient does not reach statistical significance. Nonetheless, it is interesting that the raw gap among Ph.D. holders is smaller than in the overall population and among graduates due to females' characteristics that reduce the gap.

The decomposition of the gap allows us to inspect the role exercised by the control variables more accurately. In this regard, a second result concerns the coefficient of the unexplained part of the gap, assuming positive values around 4% (ranging from 3.9 to 4.7%). This means that regardless of the controls included in the analysis, we find wage discrimination against women. Compared with the results provided by the few existing studies on the GWG among Ph.D. holders, our findings suggest that the unexplained gap in Italy is lower than that observed in the UK (where it is approximately 11 log percentage points; Schulze 2015) and lower than that found in the US (where yearly salaries of women are about \$10,000 dollars below those of men; Webber and Canchè 2015). Our results are pretty similar to those found by recent analyses focused on university graduates in Italy. For example, Piazzalunga (2018) detects an unexplained wage gap of

Table 1: Oaxaca–Blinder decomposition results on full sample.

	(1)	(2)	(3)	(4)	(5)
	Log Hour wage	Log Hour wage	Log Hour wage	Log Hour wage	Log Hour wage
Men	2.253*** (313.38)	2.253*** (313.38)	2.255*** (307.81)	2.255*** (307.81)	2.233*** (263.09)
Women	2.225*** (328.16)	2.225*** (328.16)	2.231*** (320.95)	2.231*** (320.95)	2.216*** (278.15)
Difference	0.0281*** (2.84)	0.0281*** (2.84)	0.0240** (2.37)	0.0240** (2.37)	0.0166 (1.43)
Explained	-0.0168*** (-4.94)	-0.0152*** (-3.41)	-0.0232*** (-3.80)	-0.0228*** (-3.72)	-0.0220*** (-3.01)
Unexplained	0.0449*** (4.47)	0.0433*** (4.22)	0.0472*** (4.88)	0.0468*** (4.85)	0.0386*** (3.42)
Observations	7950	7950	7700	7700	5564
Background	X	X	X	X	X
Demographic	X	X	X	X	X
Education		X	X	X	X
Job-related variables			X	X	X
Vertical mismatch				X	X
Years of experience					X

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Background controls are: parents education, parents job status, high school diploma. Demographic controls are: married, living alone, offspring, macro-region, age. Education controls are: 2006 cohort, degree vote, area of Ph.D., scholarship during Ph.D., visiting during Ph.D., teaching during Ph.D., Ph.D. in time. Job-related variables are: academic job, migration, self-employment, fixed-term, public job, job position. Vertical mismatch controls are: overeducation, overskilling.

5.6% among university graduates. Our finding would then suggest that the GWG lowers only very slightly once more educated people are considered.

A third interesting result is that the coefficient of the explained difference is always negative (ranging from -1.5% to -2.3% , increasing as we include job-related variables). This means that, on average, women are more endowed than men with characteristics associated with a higher wage. This is the reason why when the raw difference between wages is not statistically significant, its unexplained part is still positive and significant. In other words, if women had the same characteristics as men, they would have an even lower wage. By taking a more detailed look at the estimates, it turns out that controlling for job-related variables (Table 1, col. 3) makes the (negative) explained gap larger. While this finding might depend on the slight change of the sample size that is observed when moving from Col. 2 to Col. 3., it would indicate that women are holding better job positions than men, i.e., job positions that would reduce the gap if remunerated the same. Furthermore, contrary to the existing literature (Addabbo and Favaro 2011), the inclusion of working experience does not seem to have a sizable impact on the explained part of the gap. However, it is worth noting that this result may be due to missing data altering the sample size in Col. 5.

The detailed coefficients of the decomposition are not reported for the sake of space, but the variable that most dramatically affects the negative coefficient of the explained part is holding an academic job, whose impact is estimated at between -1.4% and -2.6% in Columns (3) and (5), respectively. This finding suggests a need for separate sub-sample analyses focused on those working in the academic sector and those working in the non-academic sectors.

Table 2 reports the results of the O–B decomposition performed on the sub-sample of academic jobholders. We follow the same strategy adopted before by progressively adding a set of controls in each specification. Here, the raw difference in wages is statistically significant in all the estimates, taking values between 5.2 and 6.3%, almost double that estimated on the full sample. Columns (1) and (2) show that background, demographic, and education controls do not account for the difference in wages (5.2%), which here is mostly unexplained. Meanwhile, as reported in Column (3), the inclusion of job-related variables results in a positive and statistically significant explained part (1.7%), which accounts for just a third of the raw difference (5.2%). In comparison, the remaining two-thirds (3.5%) of the raw gap is due to discrimination against women. A similar result can be observed in Column (4). In Column (5), the analysis is performed with the inclusion of years of experience, which results in a larger raw difference (6.3%), a larger explained part (2.9%, which is about 45% of the raw difference), and an unexplained part somewhat comparable to the previous estimation (3.4%).

Table 2: Oaxaca – Blinder decomposition results on the sub-sample of academic job.

	(1)	(2)	(3)	(4)	(5)
	Log Hour wage	Log Hour wage	Log Hour wage	Log Hour wage	Log Hour wage
Men	2.117*** (205.10)	2.117*** (205.10)	2.117*** (205.10)	2.117*** (205.10)	2.122*** (189.27)
Women	2.065*** (211.52)	2.065*** (211.52)	2.065*** (211.52)	2.065*** (211.52)	2.059*** (194.45)
Difference	0.0519*** (3.65)	0.0519*** (3.65)	0.0519*** (3.65)	0.0519*** (3.65)	0.0628*** (4.07)
Explained	-0.00670 (-1.41)	0.000392 (0.06)	0.0173** (2.36)	0.0175** (2.37)	0.0287*** (3.39)
Unexplained	0.0586*** (4.00)	0.0515*** (3.43)	0.0346** (2.40)	0.0344** (2.39)	0.0341** (2.13)
Observations	3023	3023	3023	3023	2453
Background	X	X	X	X	X
Demographic	X	X	X	X	X
Education		X	X	X	X
Job-related variables			X	X	X
Vertical mismatch				X	X
Years of experience					X

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Background controls are: parents education, parents job status, high school diploma. Demographic controls are: married, living alone, offspring, macro-region, age. Education controls are: 2006 cohort, degree vote, area of Ph.D., scholarship during Ph.D., visiting during Ph.D., teaching during Ph.D., Ph.D. in time. Job-related variables are: migration, fixed-term, job position. Vertical mismatch controls are: overeducation, overskilling.

In summary, we find that women Ph.D.s who work in the academic sector have a raw wage which is lower than that of men by 5 or 6 percentage points and that at least half of this gap cannot be explained by the difference in skills, endowments, or job positions. The size of this unexplained gap is in line with the findings provided by Schulze (2015) when looking at the UK academic sector. Nevertheless, in that case, the unexplained gap turned out not to be statistically significant, whereas, in our analysis, a high statistical significance is observed. While the size of the unexplained gap retrieved by our calculations is not striking, such evidence is in line with the work by previous scholars who investigated pointed out gender inequality in academia by focusing on the earnings gap (Tao 2018) and career advancements (Bain and Cummings 2000; Ginther and Kahn 2004).

The results for the sub-sample of those working outside the academic sector are printed in Table 3. As before, the different columns report the results from specifications, progressively including new sets of variables. Consistent with the descriptive information provided in Section 4, the data in the table reveals that for both men and women, the net hourly wage in the non-academic sector is higher than that observed in universities. This is particularly evident for women. As an effect, the raw difference between wages is lower than that estimated for the academic sector. The decomposition of the wage difference adds more nuance to this result: the explained part is negative in all the estimations and decreases with the inclusion of the job-related variables. At the same time, the unexplained part is always positive and statistically significant and ranges from a minimum of 4.4% in Column (5) to a maximum of 5.8% in Column (3). On the one hand, this finding is consistent with the idea that the unexplained GWG is higher in non-academic sectors than in academia (Schulze 2015). On the other hand, it is worth noting that the size of the gap observed by our analysis is remarkably smaller than the gap suggested by previous analyses based on different national contexts (Schulze 2015; Webber and Canché 2015).

The coefficients of the decomposition, which are not reported in order to save space, show that the negative sign of the explained part is driven by engineering specialists (−1.6%), self-employed (−0.7%) and public job (−1%). The latter finding is probably due to women being overrepresented in public non-academic jobs (around 60% of women against 40% of men), where the wages are on average 22% higher than non-public non-academic careers. We also find a negative contribution of public jobs for the unexplained part (−2.1%), which is given by the difference in returns for working in the public sector between women and men.

Both concentration and lower-wage penalty in the public sector are consistent with results detected by Jones, Makepeace, and Wass (2018) on doctorates in the UK. These results are also consistent with the evidence provided in a recent study

Table 3: Oaxaca –Blinder decomposition results on the sub-sample of non-academic job.

	(1)	(2)	(3)	(4)	(5)
	Log Hour wage	Log Hour wage	Log Hour wage	Log Hour wage	Log Hour wage
Men	2.345*** (251.19)	2.345*** (251.19)	2.352*** (244.65)	2.352*** (244.65)	2.334*** (195.30)
Women	2.315*** (269.52)	2.315*** (269.52)	2.330*** (262.11)	2.330*** (262.10)	2.324*** (220.14)
Difference	0.0295** (2.32)	0.0295** (2.32)	0.0220* (1.68)	0.0220* (1.68)	0.00962 (0.60)
Explained	-0.0206*** (-4.63)	-0.0184*** (-3.09)	-0.0356*** (-4.52)	-0.0355*** (-4.46)	-0.0342*** (-3.35)
Unexplained	0.0501*** (3.91)	0.0479*** (3.68)	0.0576*** (4.48)	0.0575*** (4.49)	0.0438*** (2.81)
Observations	4927	4927	4677	4677	3111
Background	X	X	X	X	X
Demographic	X	X	X	X	X
Education		X	X	X	X
Job-related variables			X	X	X
Vertical mismatch				X	X
Years of experience					X

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Background controls are: parents education, parents job status, high school diploma. Demographic controls are: married, living alone, offspring, macro-region, age. Education controls are: 2006 cohort, degree vote, area of Ph.D., scholarship during Ph.D., visiting during Ph.D., teaching during Ph.D., Ph.D. in time. Job-related variables are: migration, self-employment, fixed-term, public job, job position. Vertical mismatch controls are: overeducation, overskilling.

on the wage gap in Italy during the years of the economic crisis (2008–2012) (Piazzalunga and Di Tommaso 2019).

On the other hand, an engineering specialist is associated with a positive unexplained wage difference (1.5%), alongside being a manager (1.1%), being a specialist in mathematics and physics (0.7%), and being a specialist in human and social sciences (3.0%), which includes law and economic professionals. Therefore, net of the potential bias due to segregation (women's representation in these professions is 37, 39, 44, and 50%, respectively), women Ph.D. holders who find non-academic jobs in such sectors suffer an unexplained wage penalty. The results of Column (5) suggest that including years of experience reduces the unexplained gap; however, it still results in the sizable figure of 4.3%, which confirms the intuition that gender discrimination is higher outside academia than within it.

As highlighted in section two, part of the existing literature on gender discrimination in education and employment has addressed segregation by field of study (i.e., horizontal segregation; Charles and Bradley 2009; Davies and Guppy 1997). Nevertheless, the descriptive analysis of data provided above does not show any remarkable horizontal segregation, at least when dividing fields of study into STEM and non-STEM. To check whether this means that the GWG in those two macro-areas is similar, we performed several additional analyses, subdividing the sample into STEM and non-STEM fields of specialization (see footnote 11 for details). Table 4 reports the results of the full model for different sub-samples. Column (1) reports the results for non-STEM sectors (both academic and non-academic jobs), which highlight a 4% unexplained difference, counterbalanced by a negative coefficient for the explained part (−2.2%). This discrimination for doctorates awarded in non-STEM areas is much higher for non-academic jobs than for academic jobs. Column (3) shows the highest value for the unexplained part, suggesting that women who achieved a Ph.D. in non-STEM areas and have a non-academic job suffer from the most considerable wage discrimination. This sub-sample includes law and economic professions; in fact, the unexplained coefficient for high-skilled jobs in these sectors drives the result for the unexplained part (5.7%), together with overskilling (13%). Column (2), meanwhile, reports the results for non-STEM Ph.D.s who work in the academic sector. In this case, the raw difference has a sizable magnitude (5.2%). The explained term amounts to 3.3% (about 63% of the raw difference), while the unexplained term (1.9%) fails to reach statistical significance.

Column (4) reports the results of the estimation performed on all STEM areas (both academic and non-academic jobs), which show a negative explained part (−1.9%) and a positive unexplained part (3.6%). Therefore, discrimination in STEM areas seems to be lower than in non-STEM areas. Unlike non-STEM areas, the unexplained part is larger in academia than outside academia, as shown in

Table 4: Oaxaca–Blinder decomposition results by area of Ph.D.

	Non-STEM Ph.D.			STEM Ph.D.		
	(1) Log Hour wage (overall)	(2) Log Hour wage (academic job)	(3) Log Hour wage (non-academic job)	(4) Log Hour wage (overall)	(5) Log Hour wage (academic job)	(6) Log Hour wage (non-academic job)
Men	2.249*** (137.33)	2.139*** (106.94)	2.382*** (93.63)	2.224*** (230.07)	2.111*** (160.29)	2.314*** (176.19)
Women	2.230*** (161.48)	2.087*** (112.16)	2.358*** (126.22)	2.208*** (228.00)	2.038*** (168.42)	2.308*** (180.68)
Difference	0.0183 (0.86)	0.0517* (1.89)	0.0234 (0.74)	0.0167 (1.22)	0.0729*** (4.08)	0.00628 (0.34)
Explained	-0.0216* (-1.76)	0.0326** (2.26)	-0.0452** (-2.44)	-0.0192** (-2.04)	0.0325*** (2.86)	-0.0252** (-1.98)
Unexplained	0.0400** (1.97)	0.0190 (0.67)	0.0686** (2.43)	0.0359*** (2.73)	0.0404** (2.25)	0.0314* (1.71)
Observations	1995	1010	985	3569	1443	2126
Background	X	X	X	X	X	X
Demographic	X	X	X	X	X	X
Education	X	X	X	X	X	X
Job-related variables	X	X	X	X	X	X
Vertical mismatch	X	X	X	X	X	X
Years of experience	X	X	X	X	X	X

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Background controls are: parents education, parents job status, high school diploma. Demographic controls are: married, living alone, offspring, macro-region, age. Education controls are: 2006 cohort, degree vote, area of Ph.D., scholarship during Ph.D., visiting during Ph.D., teaching during Ph.D., Ph.D. in time. Job-related variables used in columns (1) and (4) are: academic job, migration, self-employment, fixed-term, public job, job position. Job-related variables used in columns (2) and (5) are: migration, fixed-term, job position. Job-related variables used in columns (3) and (6) are: migration, self-employment, fixed-term, public job, job position. Vertical mismatch controls are: overeducation, overskilling.

Columns (5) and (6), respectively. Therefore, it seems that the larger discrimination bias found in the non-academic sector is driven by non-STEM Ph.D.s, particularly those in Economics and Law.

6.2 Selection Adjusted O–B Decomposition

It is widely acknowledged that the GWG may depend on differences in labor force participation and horizontal segregation between men and women (Bobbitt-Zeher 2007; Gerber and Schaefer 2004). Not accounting for such differences may result in biased estimates of the GWG (Mussida and Picchio 2014; Olivetti and Petrongolo 2008). We acknowledge that such mechanisms may be in place regarding selection into employment and selection into Ph.D. area. In these cases, the low participation of women in the labor force and in STEM Ph.D.s may drive down the estimated gender gap. Such issues may be of marginal importance in our dataset, given that we analyze a group highly homogeneous in terms of education and experience that is characterized by a low unemployment rate (7.5%).

Nevertheless, it is worth noting that looking at our data women are overrepresented among the unemployed (they are 65% of the unemployed). Meanwhile, they are not underrepresented in STEM sectors, where they represent 52.6% of the observations. See descriptive statistics provided in Annex 2 for further details.

Keeping in mind such caveats, we estimate four different Heckman corrected O–B decompositions. The selection of women into the labor force and Ph.D. areas is modeled first as a function of background variables and then as a function of demographic variables. Column (1) of Table 5 reports the coefficient of an O–B decomposition adjusted for women selection in labor force participation, estimated using background variables as exclusion restriction. The results indicate a raw gap of 4.9%, a negative explained term of -1.7% , and an unexplained term of 6.6%. In Column (2) the same estimation is performed by including the demographic variables in the selection equation, which results in a raw gap of 6.9%, a negative explained term of 1.8% and an unexplained term of 8.8%. Compared to the result of the unadjusted O–B decomposition in Column (5) of Table 1, the unexplained term is substantially larger in both the selection adjusted estimations, suggesting that not accounting for women’s self-selection into employment results in an upward biased wage equation for women.

Column (3) reports the results of an analysis performed on STEM areas only, where women selection into STEM Ph.D. programs is accounted for by background controls. The adjusted O–B decomposition results in a raw difference of 6.8%, a negative explained term of 1.2% and an unexplained term of 7.9%. Column (4) gives the results of the same estimation, with demographic controls as exclusion

Table 5: Selection-adjusted Oaxaca –Blinder decomposition results.

	(1)	(2)	(3)	(4)
	Log Hour wage (Overall)	Log Hour wage (Overall)	Log Hour wage (STEM Ph.D.)	Log Hour wage (STEM Ph.D.)
Men	2.233*** (260.81)	2.233*** (260.77)	2.224*** (227.32)	2.224*** (227.26)
Women	2.184*** (76.06)	2.164*** (110.90)	2.157*** (54.14)	2.134*** (77.87)
Difference	0.0491 (1.64)	0.0691*** (3.25)	0.0675* (1.65)	0.0906*** (3.11)
Explained	-0.0168** (-2.44)	-0.0184*** (-2.60)	-0.0115 (-1.30)	-0.0121 (-1.31)
Unexplained	0.0659** (2.22)	0.0875*** (4.16)	0.0791* (1.94)	0.103*** (3.56)
Observations	5564	5564	3569	3569
Background	Selection equation	X	Selection equation	X
Demographic	X	X	X	X
Education	X	X	X	X
Job-related variables	X	X	X	X
Vertical mismatch	X	X	X	X
Years of experience	X	X	X	X

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Background controls are: parents education, parents job status, high school diploma. Demographic controls are: married, living alone, offspring, macro-region, age. Education controls are: 2006 cohort, degree vote, area of Ph.D., scholarship during Ph.D., visiting during Ph.D., teaching during Ph.D., Ph.D. in time. Job-related variables are: academic job, migration, self-employment, fixed-term, public job, job position. Vertical mismatch controls are: overeducation, overskilling.

restrictions. In this case, the raw gap amounts to 9.0%, the explained component is negative and equals 1.2%, while the unexplained component amounts to 10.3%. These results can be compared to Column (4) of Table 4, and show that, after accounting for horizontal segregation in the field of Ph.D. studies, the gender wage gap is at least three times larger (3.4% is the unexplained part of the unadjusted estimation).

6.3 Quantile Decomposition

The O–B decompositions provided thus far have reported the average GWG. To complete the analysis, we provide a graphical representation of the GWG decomposition along with the wage distribution of our sample. Figure 1 displays the coefficients estimated for the full sample (upper panel), the sub-sample of STEM Ph.D. holders (lower-left panel), and the sub-sample of non-STEM Ph.D. holders. For the full sample, we notice considerable discrimination at the very low end of the distribution, followed by a small but persistent unexplained difference in wages in the first third of the distribution, and a soaring difference in the last 20%, driven by a negative explained coefficient and an unexplained positive coefficient.

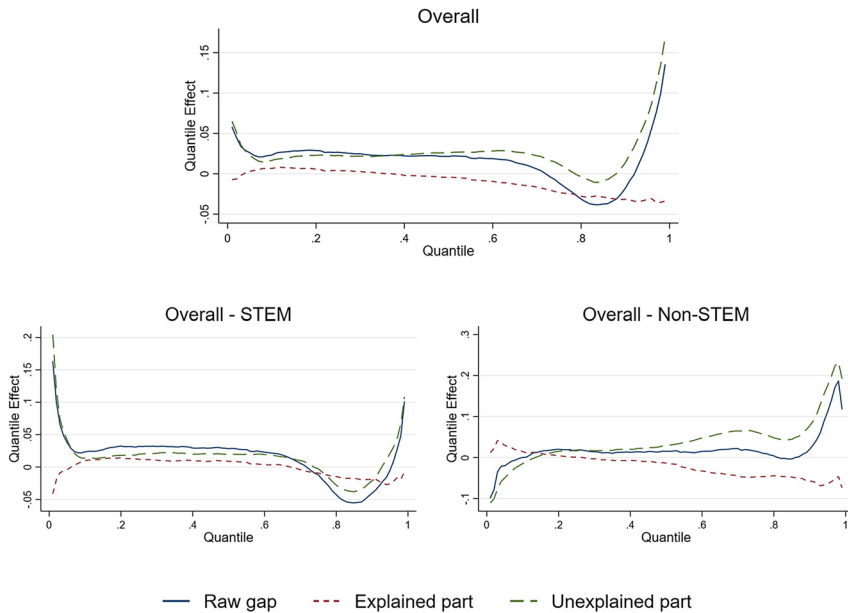


Figure 1: Quantile decomposition results on the full sample.

A somewhat similar pattern is observable for STEM Ph.D.s, but with a much larger difference at the beginning of the distribution and a less steep decline after the first few percentiles. A substantial difference is observed for non-STEM Ph.D.s, where a negative gap can be observed at the beginning of the distribution, then a substantially flat raw difference around zero that can be decomposed in a negative explained part and a positive unexplained part, meaning that women have better endowments which are not paid for. Again, in the highest 20% of the wage distribution, the wage differential between men and women and its unexplained part shows a steep increase, while the explained part shows a slight decrease. Therefore, in the full sample, we observe a tendency to wage inequality between men and women at lower wages, which is driven by STEM areas. At the same time, we observe a glass-ceiling effect at higher wages, in both STEM and non-STEM areas, with a higher magnitude observed for the latter.

Figure 2 displays the coefficients of the quantile decomposition performed on the sub-sample of academic jobholders. In the upper panel, both STEM and non-STEM Ph.D. areas are included in the sample. The raw difference in wages is constant and completely explained (around 5%) in the first third of the distribution, and shows a slowly increasing pattern, which for the top 20% of the

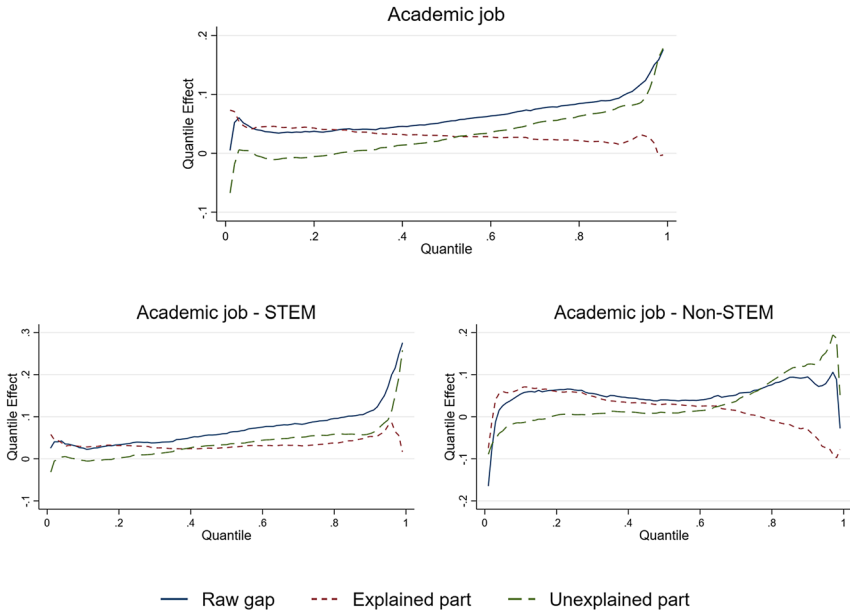


Figure 2: Quantile decomposition results on the sub-sample of academic jobs.

distribution reaches a raw difference of 10%, almost entirely due to discrimination against women. At the tail of the distribution, the difference and its unexplained part increase even more steeply. When we only consider the academic personnel who graduated in STEM areas (lower-left panel of Figure 2), we observe a very similar trend to that of the full sample, with the only significant difference around the 50th percentile where the explained part also increases. At the tail of the distribution, the explained part twists and shows a decreasing trend, while the raw difference and unexplained part soar to more than 20%. This dramatic twist has to be taken with a grain of salt, given the low numerosity of the sample at that point in the distribution. Similar to what happens for STEM areas, with non-STEM Ph.D.s with academic jobs (lower-right panel), we observe a negative gap at the very beginning of the distribution, followed by a positive raw gap, which is entirely explained. Nevertheless, the raw difference remains roughly constant up to the 80th percentile and then shows a minimal increase. The explained part of such raw difference decreases along with the distribution, while the unexplained part increases.

Finally, we perform the quantile decomposition on the sub-sample of non-academic jobholders. Their results are plotted in Figure 3, where we distinguish

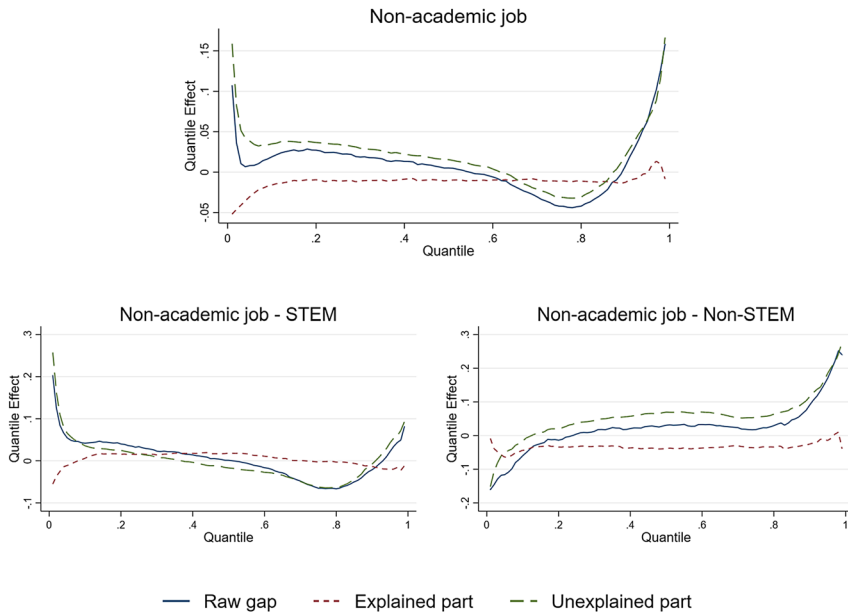


Figure 3: Quantile decomposition results on the sub-sample of non-academic jobs.

between the sub-sample of STEM Ph.D.s (lower-left panel) and the sub-sample of non-STEM Ph.D.s (lower-right panel). On all non-academic job holders (upper panel), we observe a sizable raw difference entirely unexplained at the beginning of the distribution (together with a negative coefficient for the explained part). Along with the distribution, it decreases (becoming negative at the 60th percentile). Instead, it increases in the last 10% of the distribution, where the gap soars, reaching 15% due to discrimination against women. Regarding STEM Ph.D.s, the wage differential follows the same pattern at the beginning of the distribution; the GWG then declines, approaches zero, and becomes negative around the 50th percentile, up to the 90th percentile. The coefficient computed on the sub-sample of non-STEM areas shows a different trend. The gap is negative at the beginning of the distribution; it then increases steeply and reaches zero around the 20th percentile. However, the unexplained part is positive and has a magnitude of between 5 and 10% due to an explained coefficient that is constantly negative along with the distribution. The gap remains steady up to the 80th percentile, when it rises to over 20%, together with its unexplained component.

Overall, the quantile decomposition analysis confirms that differences among Ph.D. areas and job types are relevant for assessing the GWG among Ph.D. holders. It also adds to the investigation that heterogeneity within the wage distribution can be appropriate in some sectors. More precisely, STEM Ph.D.s working in academia experience a GWG that steadily increases along with the whole distribution, with a spike in the tail, suggesting that women in this sector may face a hurdle in accessing not only the best-paid jobs (as also happen for non-STEM Ph.D. holders in academia), but also jobs with higher-than-average wages.

Outside academia, the situation is more nuanced. For STEM Ph.D. holders, we detect the highest GWG at the beginning of the distribution, suggesting that this sector may have a sticky floor for women. However, it appears that for those who overcome this obstacle, the level of discrimination is relatively small, except in the case of the best-paid jobs. Meanwhile, Ph.D. holders in non-STEM areas that work outside of academia face small but constant gender discrimination and a glass ceiling when approaching the best-paid jobs. Suppose we exclude non-STEM Ph.D.s in the academic sector. In that case, the glass ceiling is a consistent result, suggesting that even among those with the highest level of education, the chances of accessing the best-paid jobs are not equal between men and women.

7 Conclusion

Educational differences are considered one of the leading causes of wage discrimination between men and women (Blau and Kahn 2017). If women and men

have unequal educational attainments, it is more likely that women suffer from discrimination and exclusion from the best-paid jobs. Nevertheless, scholars have demonstrated that a GWG also exists among people with the same level of education (de la Rica et al. 2008; Garcia-Prieto and Gómez-Costilla 2017; Mussida and Picchio 2014).

While some scholarly contributions have suggested that one of the higher education returns is lower gender discrimination, recent research has challenged this view (Piazzalunga 2018). Within this context, our article contributes to the discussion by analyzing the gender wage gap among the most educated population segment in Italy, i.e., Ph.D. holders, at the start of their working careers.

The evidence provided by our analysis suggests that a negative relation between educational attainment and the gender wage gap cannot be taken for granted, at least in Italy. Even women who have recently graduated at the highest level of education (Ph.D.) suffer from wage discrimination, and its magnitude is in line with that estimated for college graduates (Piazzalunga 2018).

Our study also offers insights into the determinants of the wage gap observed among Italian Ph.D. holders. Indeed, most 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. However, that is not the case, and in-depth inspection of data reveals an even more dramatic picture than appears at first glance. The explained component of the raw gap is often negative, suggesting that women Ph.D.s, on average, have higher endowment than men, and this compensates for part of the raw wage gap. For this reason, gender discrimination may be at work even when the raw wages are similar between men and women.

Nevertheless, such evidence concerns Ph.D. holders taken as an aggregate and, while important, potentially misses essential nuance.

As regards the scientific areas of study, unlike the literature on college graduates, we do not observe concentration in non-STEM areas; moreover, women who graduated in these areas suffer more considerable wage discrimination, specifically when employed outside of academia.

Overall, some significant differences emerge between academia and non-academic sectors: in the former, the raw wage difference is at least partially explained by observable characteristics such as job position, whereas in the latter such observable characteristics contribute to discrimination because endowments are not rewarded with equal pay for both men and women (i.e., the explained part of the decomposition is always negative). Therefore, the full sample results are probably driven by the conditions of women working outside of academia, where the wage gap would be even higher if the capital endowment of women was lower.

One may conclude that academia is a relative shield against the gender wage gap; nonetheless, other forms of gender discrimination may rise inside the academic sector. In Italy, public academic jobs are regulated by the labor rules of the public sector, which allow limited discretion in wage setting. More generally, this is true for all public sector jobs, so that, unsurprisingly, our estimations also show that wages in public, non-academic jobs are 20% higher than in the private sector. However, also in the public sector, men and women may face different opportunities for career advancement. Our results show that men hold the best-paid position in the academic sector, which explains the raw wage gap and suggests that women are less likely to achieve a promotion. This raises the doubt that lack of access to the best position hinders women's progress in the academic career, a question that falls outside the scope of this paper and calls for further research.

Additionally, it has been observed that during the 2009–12 economic crisis, the public sector premium was decreased due to austerity measures, and this mainly impacted women's wages (Piazzalunga and Di Tommaso 2019). This suggests that further research ought to inspect the dynamic of the wage gap in the academic sector in the long run to provide a fully comprehensive picture.

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. This is true for the overall sample and its sub-aggregates, except for non-STEM Ph.D.s working in the academic sector.

Some limitations of our study should be kept in mind. First, these analyses are based on self-reported information that might be biased because of measurement error. The high rate of non-responses observed for some variables confirms the idea that self-reported information has significant limitations. Second, our analysis fails to take into account the subjective working motivations and aspirations of Ph.D. workers. These unobserved variables may, of course, have a significant impact on workers' reservation wage and willingness to improve their job conditions.

Despite these limitations, our findings indicate that the GWG also persists at the doctoral level in Italy. More specifically, they suggest that the monitoring of gender differences in the evolution of Ph.D. holders' occupational careers requires adequate attention. In this perspective, it would be valuable for future analyses to focus on disparities in Ph.D. holders' labor market outcomes, such as perceived working conditions, job stability, autonomy at work, and job satisfaction. Such monitoring may facilitate tailored policies for the specific issues revealed by particular groups of Ph.D. workers.

Annex 1

Table 6: Descriptive statistic of demographic and background variables.

Variable	Categories	Men			Women			Total		
		N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Parents education	Parents without degree (base category)	4075	0.592	0.492	4739	0.605	0.489	8814	0.599	0.49
	One parent with degree	4075	0.201	0.401	4739	0.2	0.4	8814	0.201	0.401
	Both parents with degree	4075	0.207	0.405	4739	0.195	0.396	8814	0.2	0.4
Parents job status	Parents not working (base category)	4075	0.095	0.294	4739	0.104	0.306	8814	0.1	0.3
	One parent working	4075	0.45	0.498	4739	0.445	0.497	8814	0.447	0.497
	Both parents working	4075	0.455	0.498	4739	0.45	0.498	8814	0.452	0.498
High school diploma	Liceo Classico	4075	0.24	0.427	4739	0.325	0.469	8814	0.286	0.452
	Liceo Scientifico	4075	0.516	0.5	4739	0.471	0.499	8814	0.492	0.5
	Liceo Linguistico	4075	0.007	0.081	4739	0.038	0.191	8814	0.023	0.151
	Istituto Magistrale	4075	0.008	0.09	4739	0.051	0.22	8814	0.031	0.174
	Istituto Tecnico	4075	0.204	0.403	4739	0.087	0.282	8814	0.141	0.349
Married	Istituto Professionale	4075	0.017	0.129	4739	0.014	0.118	8814	0.015	0.123
	Istituto d'arte	4075	0.002	0.044	4739	0.003	0.054	8814	0.002	0.05
	Liceo Artistico (base category)	4075	0.005	0.07	4739	0.01	0.098	8814	0.007	0.086
Living alone	–	4075	0.559	0.497	4739	0.649	0.477	8814	0.607	0.488
	–	4075	0.248	0.432	4739	0.18	0.385	8814	0.211	0.408
Offspring	No children (base category)	4075	0.682	0.466	4739	0.594	0.491	8814	0.635	0.482
	One child	4075	0.186	0.389	4739	0.245	0.43	8814	0.218	0.413
Macro-region	Two children or more	4075	0.132	0.338	4739	0.161	0.368	8814	0.148	0.355
	North	4075	0.374	0.484	4739	0.376	0.484	8814	0.375	0.484
	Centre (base category)	4075	0.238	0.426	4739	0.25	0.433	8814	0.244	0.43
	South	4075	0.388	0.487	4739	0.375	0.484	8814	0.381	0.486

Table 6: (continued)

Variable	Categories	Men			Women			Total		
		N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Age	Less than 30 years (base category)	4075	0.279	0.448	4739	0.286	0.452	8814	0.283	0.45
	30 years	4075	0.15	0.357	4739	0.152	0.359	8814	0.151	0.358
	31 years	4075	0.136	0.343	4739	0.141	0.348	8814	0.139	0.346
	32 years	4075	0.104	0.305	4739	0.112	0.316	8814	0.108	0.311
	More than 32 years	4075	0.332	0.471	4739	0.309	0.462	8814	0.319	0.466

Table 7: Descriptive statistics for job-related variables.

Variable	Categories			Men			Women			Total		
		N	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Employed	-	4075	0.947	0.223	4739	0.916	0.278	8814	0.93	0.254		
Log Hourly wage	-	3735	2.253	0.439	4215	2.225	0.44	7950	2.238	0.44		
Academic job	-	4075	0.389	0.488	4739	0.342	0.474	8814	0.364	0.481		
Migration	-	4075	0.263	0.44	4739	0.222	0.415	8814	0.241	0.428		
Self-employed	-	4075	0.151	0.358	4739	0.106	0.308	8814	0.127	0.333		
Fixed-term	-	4075	0.361	0.48	4739	0.448	0.497	8814	0.408	0.491		
Public job	-	4075	0.522	0.5	4739	0.529	0.499	8814	0.526	0.499		
Years of experience	-	2745	1.985	1.474	3178	1.952	1.496	5923	1.967	1.486		
Job position		3761	0.002	0.046	4188	0.003	0.053	7949	0.003	0.05		
Non-skilled jobs		3761	0.017	0.129	4188	0.027	0.163	7949	0.023	0.148		
Qualified employment		3761	0.094	0.291	4188	0.094	0.292	7949	0.094	0.291		
Technical profession		3761	0.041	0.198	4188	0.023	0.149	7949	0.031	0.174		
Administrative and managerial position		3761	0.041	0.198	4188	0.032	0.175	7949	0.036	0.186		
Specialist in mathematics		3761	0.083	0.277	4188	0.045	0.207	7949	0.063	0.243		
Specialist in Engineering		3761	0.035	0.184	4188	0.051	0.219	7949	0.043	0.203		
Specialist in life science		3761	0.042	0.201	4188	0.046	0.21	7949	0.044	0.205		
Specialist in health		3761	0.101	0.301	4188	0.09	0.287	7949	0.095	0.294		
Specialist in human sciences		3761	0.138	0.345	4188	0.221	0.415	7949	0.182	0.386		
Specialist in research and teaching (base category)		3761	0.012	0.108	4188	0.006	0.075	7949	0.009	0.092		
Professor		3761	0.027	0.161	4188	0.03	0.171	7949	0.029	0.167		
Teaching professor		3761	0.165	0.371	4188	0.112	0.315	7949	0.137	0.344		
Researcher		3761	0.165	0.371	4188	0.112	0.315	7949	0.137	0.344		

Table 7: (continued)

Variable	Categories	Men			Women			Total		
		N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
	Contract researcher	3761	0.028	0.165	4188	0.024	0.154	7949	0.026	0.159
	Language assistant	3761	0.001	0.028	4188	0.002	0.044	7949	0.001	0.037
	Research assistant	3761	0.011	0.106	4188	0.013	0.114	7949	0.012	0.11
	Graduated technician	3761	0.005	0.069	4188	0.007	0.082	7949	0.006	0.076
	Research fellow	3761	0.115	0.32	4188	0.138	0.345	7949	0.128	0.334
	Post-doc grant	3761	0.03	0.169	4188	0.021	0.143	7949	0.025	0.156
	Research grant	3761	0.013	0.113	4188	0.016	0.124	7949	0.014	0.119

Table 8: Descriptive statistics for education and vertical mismatch variables.

Variable	Categories	Men			Women			Total		
		N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
2006 cohort	-	4075	0.558	0.497	4739	0.551	0.497	8814	0.554	0.497
Ph.D. in an STEM sector	-	4075	0.644	0.479	4739	0.615	0.487	8814	0.628	0.483
Area of Ph.D.	Ph.D. in Mathematics and informatics	4075	0.047	0.212	4739	0.024	0.155	8814	0.035	0.184
	Ph.D. in Physics	4075	0.083	0.276	4739	0.028	0.166	8814	0.054	0.225
	Ph.D. in Chemistry	4075	0.057	0.233	4739	0.07	0.256	8814	0.064	0.246
	Ph.D. in Earth sciences	4075	0.037	0.19	4739	0.026	0.16	8814	0.031	0.174
	Ph.D. in Biology	4075	0.073	0.26	4739	0.168	0.374	8814	0.124	0.329
	Ph.D. in Medicine	4075	0.069	0.253	4739	0.11	0.313	8814	0.091	0.287
	Ph.D. in Agricultural and veterinary sciences	4075	0.081	0.272	4739	0.08	0.271	8814	0.08	0.272
	Ph.D. in Civil engineering and architecture	4075	0.101	0.302	4739	0.083	0.275	8814	0.091	0.288
	Ph.D. in Industrial and information engineering	4075	0.095	0.293	4739	0.025	0.157	8814	0.058	0.233
	Ph.D. in Antiquities, philology, literary studies, art history	4075	0.071	0.258	4739	0.129	0.335	8814	0.102	0.303
	Ph.D. in History, philosophy, pedagogy and psychology	4075	0.088	0.284	4739	0.103	0.304	8814	0.096	0.295
	Ph.D. in Law	4075	0.081	0.273	4739	0.072	0.259	8814	0.076	0.266
	Ph.D. in Economics and statistics	4075	0.079	0.269	4739	0.052	0.222	8814	0.064	0.245

Table 8: (continued)

Variable	Categories			Men			Women			Total			
		N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Degree vote	Ph.D. in Political and social sciences (base category)	4075	0.037	0.188	4739	0.029	0.168	8814	0.033	0.177			
	66–90 (base category)	4075	0.004	0.064	4739	0.003	0.054	8814	0.004	0.059			
	91–100	4075	0.062	0.24	4739	0.042	0.201	8814	0.051	0.22			
	101–105	4075	0.114	0.318	4739	0.102	0.303	8814	0.108	0.31			
	106–109	4075	0.135	0.342	4739	0.124	0.329	8814	0.129	0.335			
Visiting during Ph.D.	110	4075	0.108	0.31	4739	0.111	0.314	8814	0.11	0.312			
	110 cum laude	4075	0.577	0.494	4739	0.618	0.486	8814	0.599	0.49			
	–	4075	0.313	0.464	4739	0.276	0.447	8814	0.293	0.455			
	Ph.D. in time	4075	0.892	0.31	4739	0.904	0.295	8814	0.898	0.302			
	Scholarship during Ph.D.	4075	0.78	0.414	4739	0.782	0.413	8814	0.781	0.413			
Overeducation	Teaching during Ph.D.	4075	0.764	0.425	4739	0.738	0.44	8814	0.75	0.433			
	–	4075	0.118	0.323	4739	0.138	0.345	8814	0.129	0.335			
	Overskilling	4075	0.394	0.489	4739	0.438	0.496	8814	0.418	0.493			

Annex 2

Table 9: Discrimination by gender in employment, STEM area and academic job.

	<i>N</i>	Women		<i>N</i>	Women
Not employed	613	65.1%	Ph.D. in a non-STEM area	3276	55.7%
Employed	8201	52.9%	Ph.D. in an STEM area	5538	52.6%
Total	8814	53.8%	Total	8814	53.8%

Table 10: Gender discrimination by Ph.D. area.

	<i>N</i>	Women
Ph.D. in Mathematics and Informatics	309	37.5%
Ph.D. in Physics	473	28.5%
Ph.D. in Chemistry	568	58.8%
Ph.D. in Earth sciences	276	44.9%
Ph.D. in Biology	1092	72.8%
Ph.D. in Medicine	801	64.9%
Ph.D. in Agricultural and Veterinary Sciences	708	53.5%
Ph.D. in Civil Engineering and Architecture	804	48.8%
Ph.D. in Industrial and Information Engineering	507	23.7%
Ph.D. in Antiquities, Philology, Literary Studies, Art History	901	67.7%
Ph.D. in History, Philosophy, Pedagogy And Psychology	848	57.5%
Ph.D. in Law	673	50.8%
Ph.D. in Economics And Statistics	567	43.6%
Ph.D. in Political And Social Sciences	287	47.7%
Total	8814	53.8%

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