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Breaking the glass ceiling? The gender wage gap in research-oriented careers for PhD graduates

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Abstract
The study investigates the gender wage gap among PhD recipients in Italy, focusing on whether research-oriented jobs mitigate wage discrimination. Utilizing data from the Professional Integration Survey of PhDs, it employs quantile and Recentered Influence Function regressions to analyze wage disparities across the wage distribution. Findings reveal a persistent gender wage gap across all quantiles, with research jobs offering a wage premium that does not entirely close the gap. The analysis contributes to understanding the impact of occupational segregation and job types on wage disparities, suggesting policy interventions to address gender wage inequalities in academia and beyond. The paper highlights the need for further research and policy efforts to achieve gender parity in professional fields, particularly high-skilled sectors like private and public research entities.

Keywords Gender wage gap · PhD employment · Research jobs · Wage discrimination · Academic labor market · Unconditional quantile regression · Wage decomposition

JEL Classification J16 · J31 · I23 · J24 · J71

Introduction

The persistence of the gender wage gap remains a widely investigated topic in labor economics, particularly puzzling in jobs requiring high levels of education and specialized skills. In particular, the demographic of PhD graduates presents a unique case. In fact, despite having similar levels of education and skills, the GWG tends to form at the very start of their careers. This early onset of wage disparity highlights the persistence of gender biases and structural inequalities in the labor market even among the most highly educated individuals. This has been shown in several countries. In the UK, the overall GWG among PhD graduates is 19%, with a larger gap for men outside academia

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compared to women (Schulze, 2015). In the USA, doctoral recipients from minority groups report lower salaries than male and majority peers, with gender and race interacting to affect salary outcomes across different fields and over time (Webber & Canché, 2015). Italian PhD graduates show a monthly wage gap where women earn on average 16% less than men, with the gap even wider at the bottom and top of the wage distribution (Passaretta & Triventi, 2021). Why does this disparity exist in labor market segments where equality of opportunity is highly valued? One explanation that has been posited is the role of occupational segregation and the types of jobs men and women tend to achieve post-PhD, with women often facing a glass ceiling effect (Castagnetti & Giorgetti, 2019). Research-oriented jobs, instead, may offer a shield against wage discrimination. Yet, the extent to which these roles influence the GWG among PhD holders remains unclear. This leads to our primary research question: How do research-oriented jobs impact the gender wage gap among PhD recipients?

To address our research question, we examine the Italian case. Italy provides a compelling scenario for understanding the role of research jobs in reducing the GWG. The Italian PhD market has evolved significantly in recent years, marked by a consistent increase in the availability of PhD programs and the strength of the connections with the non-academic job market (Ghosh & Grassi, 2020). By examining Italy, we aim to gain new insights into how expanding female participation in research roles can serve as a catalyst for broader wage equality in the labor market for PhDs, thereby offering lessons applicable to other countries facing similar challenges.

Our empirical approach utilizes a dataset from the Professional Integration Survey of PhDs conducted by the Italian National Institute of Statistics (ISTAT). This dataset includes information on the careers, family status, and other relevant variables of PhD recipients from a variety of fields and universities. We employ unconditional quantile regressions and recentered influence function (RIF) technique to analyze the wage distribution and identify the factors contributing to wage disparities across different points in the wage distribution. The results of our analysis reveal a significant and persistent GWG across all quantiles. Women earn substantially less than their male counterparts, with the gap widening at the extremes of the wage distribution. Interestingly, holding a research-oriented job does confer a wage premium, albeit one that does not entirely close the GWG. The decomposition analysis further suggests that while part of the wage gap can be explained by differences in characteristics (endowment effect), a substantial portion remains unexplained, hinting at underlying discrimination or structural barriers (coefficient effect).

Building on previous work, our study contributes to the existing literature in several key ways. Firstly, it provides a comprehensive analysis of the GWG specifically among PhD holders in Italy, a demographic that has been underexplored in previous research. Secondly, it examines the impact of research-oriented jobs on the wage gap, providing insights into whether these types of positions can mitigate wage disparities. Thirdly, our methodology, employing both quantile regression and RIF regressions, offers a nuanced understanding of how the wage gap varies across the wage distribution, rather than just focusing on average effects. Fourthly, the study adds to the literature on occupational segregation by exploring how the choice of academic versus industry jobs post-PhD impacts earnings. Finally, the paper's findings have significant policy implications, suggesting areas for intervention to reduce the GWG in academia and beyond.

The rest of the paper is organized as follows: "Literature" details the theoretical framework and reviews the relevant literature. "Data" describes the data sources, while "Methods" presents the methodological approach and a discussion of technical issues. "Estimation results" examines the results and discusses their implications. "Robustness" offers some robustness checks. Finally, "Conclusions" concludes with a summary of our findings, an exploration of policy implications and suggestions for future research.

Literature

Women's participation in the labor force has been influenced by cultural norms, tradition, and discrimination, leading to unfavorable occupational distribution and pay differentials (Oaxaca, 1973). Also, there are different likelihoods of making it to top jobs depending on different precision and frequency of signals of the skills (Bjerk, 2008). Wiswall and Zafar (2018), using data from high-ability undergraduates, find that women exhibit a higher willingness to pay for jobs offering greater work flexibility and stability, while men prioritize higher earnings growth. These job preferences relate to both college major and job choices. Consequently, a gender earnings gap arises from differing preferences and constraints regarding employment (Cook et al., 2021). Blau and Kahn (2017) summarize key findings on the GWG, noting that occupation and industry significantly explain the gap, which is more pronounced at the top of the wage distribution. This may be due to women's workforce interruptions and shorter work hours, which have a greater impact in high-skill occupations. Moreover, the probability of women securing jobs declines along the wage ladder (Gobillon et al., 2015). Juhn and McCue (2017) argue that contemporary GWG is no longer explained by traditional human capital variables (such as education and work experience), as it was in the past. Although men and women start their careers with similar earnings, the gap emerges with family formation, and when associated with children, is even larger for skilled women. Redmond and McGuiness (2019) note that while the GWG has declined over time, due to gender convergence in wage-determining characteristics, gender differences in job preferences still contribute to about 10% of the wage gap.

Education and skills are essential in understanding wage disparities, with the GWG influenced by both field of study and labor market attachment. For instance, Francesconi and Parey (2018) show that the GWG is partly driven by university field of study, as well as by factors like marriage, children, and labor market participation. In Northern Ireland, Jones and Kaya (2022) observe a narrower gender pay gap compared to the rest of the UK, which they attribute to higher productivity-related characteristics among women relative to men, although gender differences in returns to these characteristics persist. Pető and Reizer (2021) further highlight that women tend to use their cognitive skills less than men in the same occupations, a trend partially shaped by household dynamics.

Research-oriented careers also play a crucial role in economic growth and innovation, making talented individuals a key focus of policy interventions. Nisticò (2018) identifies a modest positive impact of research funding on both career pursuit and publication productivity, as funded students tend to engage more in research. Leysinger et al. (2020) underscore the value of career tracking and setting expectations to understand doctoral candidates' professional trajectories better. Academic remuneration levels influence recruitment quality; as Boyle (2008) notes, the caliber of recruited researchers depends on monetary incentives.

Given the growing diversity of motivations among doctoral candidates (Sarrico, 2022), a pivotal decision for PhD graduates is whether to continue in academia or transition to industry. Lörz and Mühleck (2019) report that family circumstances differently impact men and women in starting or stopping an academic career, while Roach and Sauermann (2010) find that a strong preference for science is predictive of a career in research, whether in industry or academia. Although research careers are associated with lower average wages compared to other fields, early-career researchers may see initial salary advantages (Lassibille, 2001). The wage disparity between academia and industry for researchers is further explored by Balsmeier and Pellens (2016), who find that a preference for science enhances the link between research orientation and earnings.

Gender differences in doctoral outcomes are notable. Goldan (2021) reports a 30.4% wage gap between male and female doctoral graduates 5 years post-graduation, driven by a wage premium for men outside academia. Inside academia, however, Schulze (2015) finds a smaller GWG for PhD holders, largely attributable to field of study, with a more significant gap at higher salary quantiles. Advanced degree returns are also shaped by undergraduate major (Altonji & Zhong, 2020), making it essential to consider PhD holders' STEM versus non-STEM specializations (Alfano et al., 2021). Despite a STEM education, women are less likely to pursue STEM occupations, with many opting for less math-intensive majors or non-STEM roles due to work-life balance preferences and residential choices (Jiang, 2021). This complexity is further illustrated by Carriero et al. (2024), who explore how the wage gap varies across research careers and fields of study. In STEM, highly paid female academics may even earn more than their white male peers (Wilcox & Forhad, 2023). Ultimately, the GWG is shaped by educational paths, occupational choices, family responsibilities, and working hours (Passaretta & Triventi, 2021), with significant portions of the gap unexplained at both the lower (sticky floor) and upper (glass ceiling) ends of the wage distribution.

Data

This study uses data from the ISTAT Professional Integration Survey of PhDs, which includes a comprehensive demographic of PhD holders from private and public Italian universities. Each wave surveys two cohorts who completed their PhDs 3 and 5 years earlier. The first wave covers about 13,000 graduates with a 70% participation rate, and the second wave includes 16,000 individuals with a response rate above 70%. The survey provides data on PhD holders' academic background, employment, geographical mobility, and family status. We focus on those employed at the time of the survey, which minimizes selectivity concerns, as 93% of respondents were employed. Of the remaining 7%, 22% were awaiting a job or training program. After excluding the self-employed, medical students, and those with missing data, our final dataset includes 18,391 valid observations.

To uncover gender disparities in labor market outcomes, we focus on the logarithm of the net monthly wage.[1] Table 1 presents summary statistics for the dependent and control variables, including breakdowns by gender and *t*-tests for equality. The dataset shows balanced gender representation, though men are overrepresented in most STEM fields. Gender parity exists in Economics and Statistics, as well as Civil Engineering and Architecture. Over 32% of both men and women received their PhD before age 30, and over 85%

[1] An alternative possibility is to combine monthly wages with weekly working hours reported by interviewees to construct a measure of individual hourly wage. In practice, the distribution of the working hours variable is rather imprecise. For instance, more than 22% of respondents declare to work less than 30 h per week; although, 60% of them declare to be in full time jobs.

Table 1 Descriptive statistics

	(1)	(2)	(3)	(4)	
	Full sample	Women	Men	Difference (3)-(2)	SE
log_monthly_wage	7.314	7.231	7.395	0.163***	(0.006)
Female	0.495				
RO_job	0.760	0.723	0.795	0.072***	(0.006)
Less than 30	0.323	0.324	0.323	−0.001	(0.007)
Not single	0.548	0.579	0.518	−0.062***	(0.007)
PhD on time	0.854	0.858	0.851	−0.007	(0.005)
Experience abroad during PhD	0.388	0.372	0.402	0.030***	(0.007)
Mathematics and Informatics	0.040	0.030	0.050	0.020***	(0.003)
Physics	0.061	0.038	0.084	0.046***	(0.004)
Chemistry	0.069	0.077	0.061	−0.017***	(0.004)
Earth Sciences	0.029	0.026	0.033	0.007**	(0.002)
Biology	0.121	0.169	0.074	−0.095***	(0.005)
Agricultural and Veterinary Sciences	0.077	0.082	0.072	−0.009*	(0.004)
Civil Engineering and Architecture	0.073	0.072	0.075	0.003	(0.004)
Industrial and Information Engineering	0.149	0.072	0.224	0.151***	(0.005)
Humanities	0.102	0.131	0.075	−0.056***	(0.004)
Philosophy Pedagogy and Psychology	0.099	0.118	0.080	−0.037***	(0.004)
Law	0.067	0.072	0.063	−0.008*	(0.004)
Economics and Statistics	0.074	0.074	0.074	−0.000	(0.004)
Ranking = 1	0.121	0.121	0.121	−0.001	(0.005)
Ranking = 2	0.115	0.108	0.122	0.014**	(0.005)
Ranking = 3	0.120	0.112	0.128	0.016***	(0.005)
Ranking = 4	0.124	0.124	0.124	−0.000	(0.005)
Ranking = 5	0.179	0.179	0.180	0.001	(0.006)
Ranking = 6	0.062	0.066	0.059	−0.007*	(0.004)
Ranking = 7	0.278	0.290	0.267	−0.023***	(0.007)
Public competition	0.590	0.602	0.578	−0.023**	(0.007)
Direct knowledge of the employer	0.067	0.063	0.071	0.008*	(0.004)
Family/friends referral	0.039	0.036	0.041	0.005	(0.003)
Professor referral	0.045	0.044	0.047	0.003	(0.003)
University referral	0.020	0.022	0.019	−0.003	(0.002)
Internship or apprenticeship	0.035	0.030	0.039	0.009**	(0.003)
Direct call from a company	0.030	0.025	0.035	0.010***	(0.003)
Internet and newspapers	0.129	0.127	0.131	0.004	(0.005)
Sending CVs	0.002	0.003	0.002	−0.002*	(0.001)
Family firm	0.008	0.007	0.008	0.001	(0.001)
Recruitment agency	0.036	0.041	0.030	−0.011***	(0.003)
Father education is bachelor	0.300	0.292	0.307	0.015*	(0.007)
Mother education is bachelor	0.242	0.245	0.239	−0.006	(0.006)
High (are you overall satisfied)	0.323	0.288	0.357	0.069***	(0.007)
Medium	0.429	0.441	0.418	−0.023**	(0.007)
Low	0.248	0.271	0.225	−0.046***	(0.006)
Willingness to do PhD again	0.705	0.676	0.734	0.058***	(0.007)

Table 1 (continued)

	(1)	(2)	(3)	(4)	
Children	0.648	0.620	0.675	0.055***	(0.007)
Observations	18,391	9108	9283	18,391	

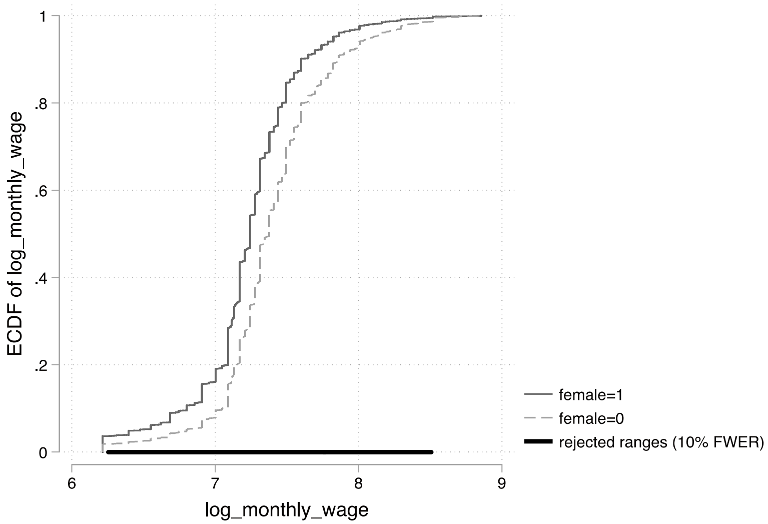

Fig. 1 Empirical CDFs of (log) monthly wage by gender and tests for equality of CDFs

completed their PhD on time. However, substantial differences emerge in research activities, with 7.2% fewer women employed in research roles compared to men.[2]

To provide preliminary evidence of differences in wage distributions associated with gender, research jobs, and fields of study, we conduct non-parametric tests of stochastic dominance based.[3] In Figs. 1, 2, and 3, black lines indicate ranges where the null hypothesis of equality is rejected. Visual inspection suggests a possible first-order stochastic dominance of male over female wage distributions, with equality rejected across the range [6.25; 8.51] (96.26% of observations). Figures 2 and 3 show similar results, rejecting equality in most wage distribution comparisons for research vs. non-research jobs and STEM vs. non-STEM fields.

[2] As we will later clarify, this unbalance in research-oriented job participation may generate gender pay disparities. Thus, selectivity corrected estimates will be presented.

[3] The G-K test is a Kolmogorov–Smirnov-type test which compares two cumulative distribution functions (CDFs) at each value, k, and tests if $F(k) = G(k)$ for all k. The testing protocol rejects equality at certain value of k while controlling for the probability of type I error (false positive), known as the family wise error rate (FWER).

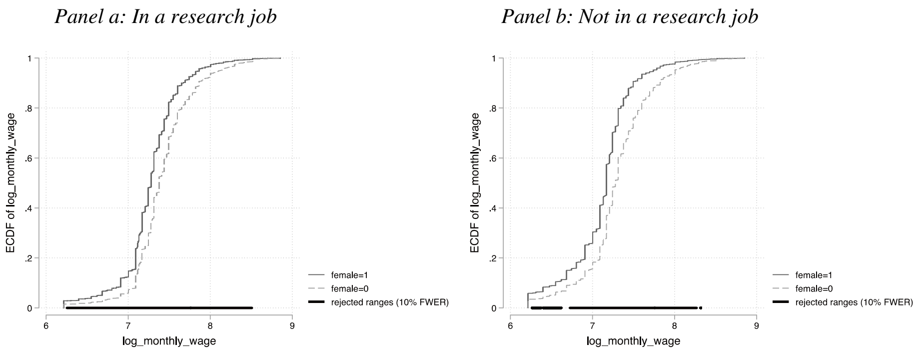

Fig. 2 Empirical CDFs of (log) monthly wage by gender and research jobs

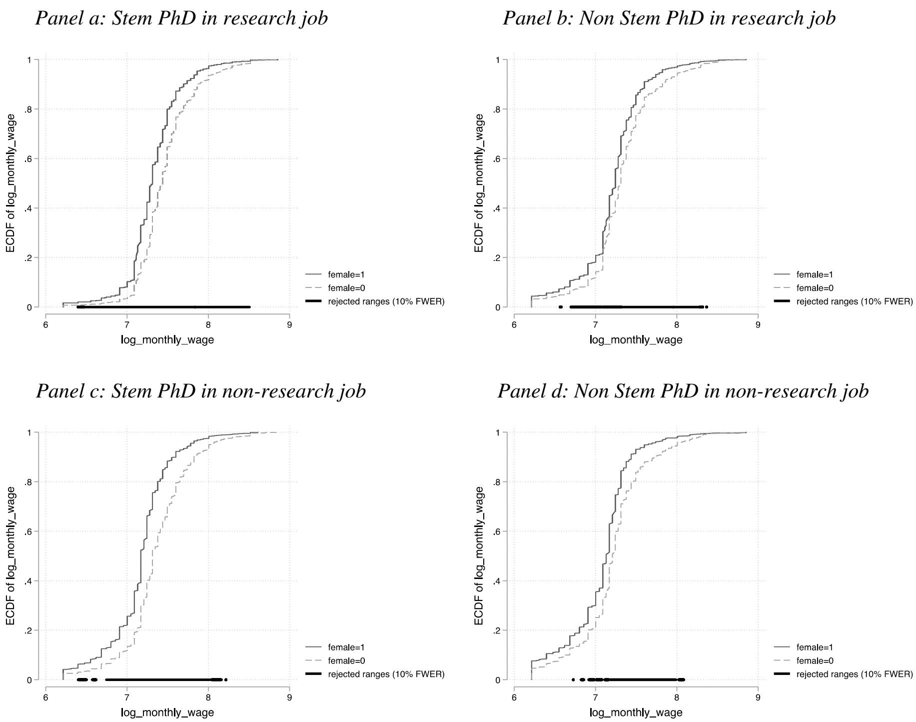

Fig. 3 Empirical CDFs of (log) monthly wage by gender, research jobs, and STEM disciplines

Methods

We analyze the GWG across the wage distribution with two complementary tools. First, unconditional quantile regressions through the *Recentered Influence Function* approach were developed by Firpo et al. (2009). Second, we decompose the gap at selected quantiles (10th, 50th, 90th) using the decomposition procedure proposed by Firpo et al. (2018). The logic behind Firpo et al. (2009) is to recenter the influence function around the quantile and

Table 2 UQR of log monthly wages—full sample

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Female	−0.107*** (0.011)	−0.087*** (0.004)	−0.182*** (0.014)
RO job	0.176*** (0.016)	0.091*** (0.005)	0.114*** (0.016)
Observations	18,391	18,391	18,391
R-squared	0.090	0.173	0.092

Estimates include university and cohort FERobust standard errors in parentheses***$p<0.01$, **$p<0.05$, *$p<0.1$

regress each observation's recentered influence on a given set of explanatory variables. In our case, the RIF regression is used to examine how research-oriented jobs affect the (log) wage at given points of the wage distribution. Analytically, the RIF for a quantile q_τ can be written as follows:

$$\mathrm{RIF}(Y;q_\tau) = \frac{q_\tau + (\tau - 1(Y < q_\tau))}{f_Y(q_\tau)}, \tag{1}$$

Where f_Y is the marginal density function of Y, $1(\bullet)$ is the indicator function, and the second addend is the influence function of the quantile (Fortin et al., 2011). Firpo et al. (2009) show that the RIF is estimated by replacing q_τ with its sample counterpart, $\hat{q}_\tau$, and f_Y is estimated with kernel methods. The *RIF regression* can be expressed as follows:

$$E\left[RIF(Y;\hat{q}_\tau)\middle|X\right] = X\beta_\tau, \tag{2}$$

Where the estimated betas measure the *unconditional quantile partial effects* and can be recovered by OLS.

Subsequently, we apply the RIF decomposition method proposed by Firpo et al. (2018), which, like the Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973), breaks down the gender pay gap into differences in characteristics (composition or endowment effect) and differences in estimated coefficients (wage structure or coefficient effect), but instead of looking at mean effects, the method extends to the entire distribution of wages.

Estimation results

We now delve into the decomposition analysis, starting with the coefficients related to the gender variable and the role-occupational dummy, as outlined in Table 2. These coefficients are estimated at the 10th, 50th, and 90th wage percentiles[4] using RIF regressions, and are presented alongside robust standard errors. The empirical evidence reveals a persistent and significant wage differential, with women's earnings consistently lagging behind those of men across the entire wage distribution.

[4] We choose to report the 10th, 50th, and 90th percentiles because glass ceiling and sticky floor effects are calculated based on such quantiles and because they make our results comparable to those in similar studies.

When the estimated coefficients are converted into percentage points, we see the wage penalty increases more steeply at the bottom and top of the wage distribution. We estimate that a 10% increase in the share of women in the sample exacerbates the gender pay gap by shifting down the wage distribution by 1.01% at the 10th quantile, 0.83% at the median, and 1.66% at the 90th quantile. This pattern suggests that even within individuals entering the labor market after completing their doctoral studies, a GWG persists, though with a differentiated impact across quantiles, pointing to systemic disparities that disadvantage women's wage potential.

The estimates also reveal a positive and significant effect of the research-oriented (RO) job dummy along the entire distribution of wages. We find that holding a research-oriented job yields a wage premium up to 19.24% higher than the salary of those employed in non-research-oriented jobs at the 10th percentile. The effect reduces to 9.5% and 12.08% at the 50th and 90th percentiles, respectively. This means that if the share of individuals in the sample holding a research job were to increase, wages at the 10th quantile of the distribution would increase faster than wages at the top.

Figure 4 plots UQR coefficients for gender (left panel) and RO job (right panel) dummies against the quantiles from the 5th to the 95th of the log wage distribution. Solid horizontal lines are the OLS estimates, while dashed lines represent the OLS 10% confidence intervals. A key finding is the non-monotonic responsiveness of the wage distribution to the gender dummy across different quantiles of the unconditional wage distribution. The GWG disfavors women at all quantiles, narrowing up to the 20th quantile before increasing steadily in absolute terms. Conversely, the quantile coefficients for the RO job variable remain positive throughout and exhibit stability after an initial decline up to the 25th quantile.

Figure 5 presents the coefficients for each field of study. Humanities is associated with negative wage effects along the entire distribution compared to the baseline category of Political and Social Sciences. For most fields of study, the wage effects are larger at the lower tail of the wage distribution. However, pronounced effects are also observed at the top of the wage distribution for Law and Economics & Statistics.

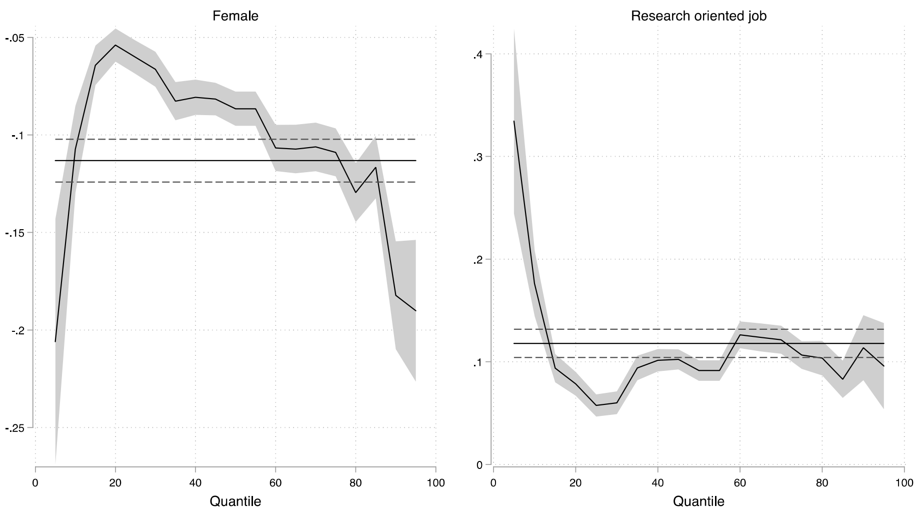

Fig. 4 UQR coefficients for female and RO job

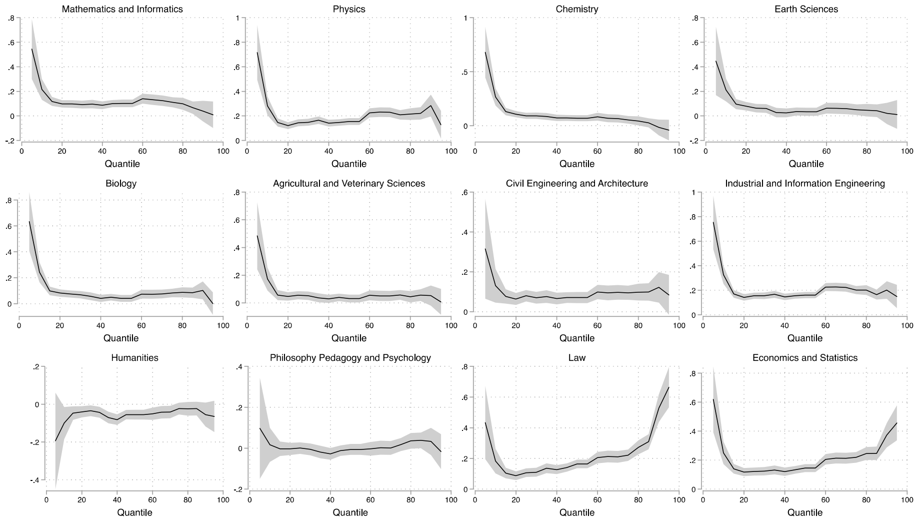

Fig. 5 UQR coefficients for fields of study. Notes: Political and Social Sciences is the baseline category

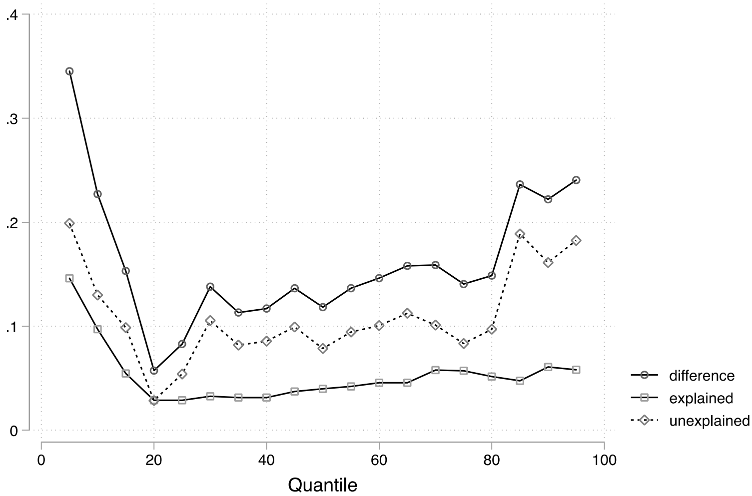

Fig. 6 Decomposition of the GWG

Table 3 UQR of log monthly wages—non-research jobs

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Female	−0.141*** (0.031)	−0.094*** (0.009)	−0.280*** (0.033)
Observations	4422	4422	4422
R-squared	0.059	0.156	0.106

Estimates include university and cohort FERobust standard errors in parentheses$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

To further explore the relationship between wages, gender, and research activities on the job, we split the data into two subsamples according to the RO job status and then run separate RIF regressions. Tables 3 and 4 report the results, which reveal several important patterns. First, at the 10th percentile, the predicted magnitude of the wage penalty is around 13% in both models (with estimated coefficients equal to − 0.141), suggesting that female PhDs earn less than their male counterparts regardless of whether they carry out R&D activities. Second, as we move to the 50th and 90th percentiles, we observe that the wage penalty first reduces and then exacerbates, and such tendency is similar in Tables 3 and 4. Third, Tables 3 and 4 allow a direct visual test of whether research-oriented (RO) employment moderates the GWG. At the 90th percentile, the wage penalty for women in non-research jobs is −0.280 log points, whereas for women in RO jobs it is only −0.139. In other words, holding a research position halves the gender gap at the top of the distribution. By contrast, at the 10th percentile the penalty is identical (− 0.141 in both models). This lets us conclude that while RO positions have little traction at the bottom of the distribution, they seem to be most effective at narrowing the GWG in the upper tail.

Table 5 confirms a *U*-shaped pattern: the raw GWG falls from 0.227 log points at the 10th percentile to 0.118 at the median, then rises to 0.222 at the 90th percentile. Endowments explain 43% (0.097/0.227) of the gap at the bottom but only 27% at the top, implying that *differences in returns* (coefficients) dominate where wages are highest. The divergent effect of research-oriented (RO) jobs on the gender wage gap (GWG) across the wage distribution, as evidenced in Tables 3 and 4, is consistent with the decomposition results presented in Table 5. At the 90th percentile, we have seen RO jobs halve the GWG, suggesting that structural barriers—captured by the rising total unexplained effect at higher quantiles (see Fig. 6)—are partially mitigated for women in research positions. In fact, there is not a statistically significant coefficient effect to RO positions at the 90th quantile. This implies that while RO jobs shield women from the full brunt of wage discrimination at the top, systemic inequalities persist, as reflected in the decomposition's finding that the coefficient effect dominates at upper quantiles (27% endowment vs. 73% unexplained effects at the 90th percentile).

Conversely, the identical penalties at the 10th percentile (− 0.141 log points in both RO and non-RO jobs) align with the decomposition's observation that the *endowment effect* (e.g., men's overrepresentation in RO jobs) exacerbates the GWG. Though RO jobs marginally reduce the gap at the bottom via the coefficient effect (higher returns for women in RO roles at the 10th percentile), this is counteracted by women's lower access to such positions. Thus, the stagnant penalty at lower quantiles reflects a dual burden: limited RO job opportunities for women (endowment) and weaker mitigating returns compared to higher quantiles.

Table 4 UQR of log monthly wages–research jobs

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Female	− 0.141*** (0.015)	− 0.075*** (0.005)	− 0.139*** (0.013)
Observations	13,969	13,969	13,969
R-squared	0.089	0.156	0.100

Estimates include university and cohort FERobust standard errors in parentheses***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5 RIF decomposition of log monthly wages

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Male wages	7.053*** (0.005)	7.382*** (0.004)	7.881*** (0.009)
Female wages	6.826*** (0.016)	7.263*** (0.003)	7.659*** (0.008)
Gender pay gap	0.227*** (0.017)	0.118*** (0.005)	0.222*** (0.012)
Endowment effect			
RO job	0.020*** (0.003)	0.007*** (0.001)	0.010*** (0.001)
Less than 30	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Not single	0.003 (0.002)	0.001 (0.000)	0.003*** (0.001)
PhD on time	−0.000 (0.000)	0.000 (0.000)	0.000(0.000)
Experience abroad during PhD	0.000 (0.001)	0.001*** (0.000)	0.004*** (0.001)
Field of study	0.074*** (0.009)	0.025*** (0.002)	0.031*** (0.006)
University ranking	0.006 (0.005)	0.001 (0.001)	0.001 (0.003)
Channel job	−0.014*** (0.005)	0.001** (0.001)	0.007*** (0.002)
Ateneo FE	0.008 (0.006)	0.003** (0.001)	0.005 (0.004)
Cohort FE	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Total explained	0.097*** (0.011)	0.040*** (0.003)	0.061*** (0.007)
Coefficient effect			
RO job	−0.122*** (0.035)	0.000 (0.009)	−0.031 (0.021)
Less than 30	0.008 (0.011)	0.002 (0.003)	0.001 (0.008)
Not single	0.061*** (0.017)	0.044*** (0.005)	0.058*** (0.012)
PhD on time	−0.043 (0.045)	−0.025** (0.012)	−0.028 (0.030)
Experience abroad during PhD	−0.002 (0.014)	0.007* (0.004)	−0.005 (0.010)
Field of study	−0.029*** (0.008)	0.005* (0.003)	−0.012* (0.007)
University ranking	0.013 (0.020)	−0.004 (0.006)	0.012 (0.018)
Channel job	−0.133*** (0.044)	−0.065*** (0.010)	−0.063*** (0.024)
Ateneo FE	0.088 (0.067)	0.020 (0.021)	0.066 (0.058)
Cohort FE	−0.000 (0.001)	−0.000 (0.000)	−0.001 (0.001)
Total unexplained	0.130*** (0.016)	0.079*** (0.005)	0.161*** (0.014)

Robust standard errors in parentheses$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

This interplay underscores that RO jobs can offer relative protection at the top; broader systemic inequities—unequal access to RO roles (endowment) and persistent discrimination (coefficient effect)—sustain the GWG. Policymakers must address both dimensions: expanding women's entry into research careers while dismantling structural biases in wage-setting.

Robustness

We acknowledge the possible self-selection bias stemming from the endogeneity of the research-oriented job variable. If PhD recipients' research career depends on unobservables that are also correlated to earned wages, the estimates presented so far should be cautiously interpreted as evidence of correlation. We attempt to correct for the bias in estimated coefficients by including selection-correction terms in the wage equations. We also employ cohort, STEM/non-STEM, and sector (academic vs. non-academic) splits purely as robustness and contextual checks. They confirm that our headline findings—a persistent GWG, mitigated (but not eliminated) by RO employment—are not driven by any single subgroup. These analyses do not aim to uncover new mechanisms specific to research-oriented careers but instead highlight conditions under which the GWG is amplified or attenuated.

Self-selection into research jobs

To address potential self-selection of PhDs into research jobs, we use a selection equation for the probability of being in a research role. Recent literature highlights two important factors influencing this decision: an individual's taste for science as a driver of research careers (Roach & Sauermann, 2010) and the impact of fertility decisions on women balancing work and family life (Adsera, 2006). Accordingly, we use the following exclusion restrictions: (i) satisfaction with competencies acquired during the PhD (high/medium/low), (ii) willingness to pursue the PhD again, and (iii) whether the PhD holder has children. The selection equation is then estimated with a probit model for men and women separately. We then compute hazard rates which are finally included as covariates. Table 6 presents the results of the selection equations. We see the exclusion restrictions perform well. In particular, the variables capturing the degree of satisfaction of the acquired competencies are positively correlated to the probability of ending up in research jobs for both women and men. The willingness to do the PhD again predicts participation in research jobs only for men, while having children is significant only in the selection equation of women. Table 7 confirms the results presented in Table 2, a persistent and significant *U*-shaped wage differential across the entire wage distribution. The research-oriented job dummy is still positive and significant, but more than doubled in magnitude. Table 8 largely confirms the results on the decomposition presented in Table 5. We can conclude then selection-corrected estimates confirm the internal validity of the empirical results.

Subsample analyses

Since there could be concerns that our estimates are sensitive to time contingent characteristics, we also present estimates for each cohort of PhDs separately in Table 9. The results confirm the existence of a gender pay gap at all estimated quantiles and for each cohort in the sample. The estimates also suggest a slight tendency to estimate a higher wage penalty for female PhDs at the 10th and 90th quantiles for the 2004 cohort. The coefficients of the RO job variable are also in line with results presented in Table 7. The cohort-based estimates corroborate the idea that our results satisfy the replicability principle. In fact, we arrive at the same findings by applying the same methods to different sets of observations, making us confident that we are truly capturing the relevant scale of the gender pay gap and the wage effect of doing research jobs. This consistency across cohorts reinforces our main conclusions while illustrating temporal stability in the GWG's persistence.

Another concern arises from the sample of PhDs including graduates from *all* disciplines. We recognize that different fields of study require different research methods that, in turn, may yield different labor market returns, especially in terms of wages. Also, we cannot exclude a priori the existence of a field-specific gender pay gap. To this end, we present separate estimates for STEM and non-STEM graduates using the estimation method

Table 6 Selection into RO job

	(1)	(2)
	Female	Male
Exclusion restrictions		
High satisfaction of acquired competencies	1.331*** (0.045)	1.405*** (0.048)
Medium satisfaction of acquired competencies	0.915*** (0.036)	0.925*** (0.039)
Willingness to do PhD again	0.034 (0.034)	0.082** (0.038)
Has children	0.140*** (0.039)	−0.038 (0.044)
Other covariates		
Less than 30	0.116*** (0.036)	0.108*** (0.039)
Not single	0.009 (0.038)	−0.022 (0.041)
PhD on time	0.087* (0.045)	0.083* (0.046)
Experience abroad during PhD	0.238*** (0.034)	0.202*** (0.036)
Mathematics and Informatics	0.049 (0.126)	0.155 (0.116)
Physics	0.130 (0.121)	0.475*** (0.108)
Chemistry	−0.079 (0.100)	0.288*** (0.111)
Earth Sciences	−0.229* (0.124)	0.151 (0.123)
Biology	−0.114 (0.090)	0.241** (0.106)
Agricultural and Veterinary Sciences	−0.168* (0.099)	0.148 (0.105)
Civil Engineering and Architecture	−0.225** (0.099)	−0.032 (0.102)
Industrial and Information Engineering	0.023 (0.102)	0.288*** (0.093)
Humanities	−0.386*** (0.091)	−0.195* (0.100)
Philosophy Pedagogy and Psychology	−0.197** (0.092)	−0.133 (0.100)
Law	−0.149 (0.099)	0.005 (0.105)
Economics and Statistics	−0.058 (0.100)	0.184* (0.105)
Ranking = 1	−0.098 (0.260)	0.453* (0.257)
Ranking = 2	−0.159 (0.208)	0.261 (0.200)
Ranking = 3	0.024 (0.214)	0.125 (0.206)
Ranking = 4	−0.055 (0.205)	0.266 (0.197)
Ranking = 5	−0.109 (0.187)	0.240 (0.176)
Ranking = 6	−0.164 (0.175)	0.129 (0.158)
Public competition	0.824*** (0.073)	0.728*** (0.084)
Direct knowledge of the employer	0.821*** (0.094)	0.498*** (0.100)
Family/friends referral	0.221** (0.102)	0.223** (0.107)
Professor referral	0.852*** (0.105)	0.620*** (0.113)
University referral	0.617*** (0.119)	0.593*** (0.142)
Internship or apprenticeship	0.308*** (0.107)	0.499*** (0.113)
Direct call from a company	0.406*** (0.116)	0.413*** (0.117)
Internet and newspapers	0.304*** (0.081)	0.338*** (0.091)
Sending CVs	−0.116 (0.260)	−0.781** (0.374)
Family firm	0.178 (0.177)	−0.293* (0.178)
Constant	−1.085*** (0.224)	−1.152*** (0.216)
Observations	9107	9283
University FE	YES	YES
Cohort FE	YES	YES

Table 7 UQR of log monthly wages with selection

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Female	−0.098*** (0.012)	−0.080*** (0.005)	−0.164*** (0.014)
RO job	0.357*** (0.040)	0.218*** (0.013)	0.480*** (0.040)
Selection	−0.126*** (0.026)	−0.090*** (0.008)	−0.229*** (0.027)
Selection squared	−0.004 (0.012)	−0.005(0.004)	0.026** (0.013)
Observations	18,390	18,390	18,390
R-squared	0.092	0.178	0.097

Estimates include University and cohort FERobust standard errors in parentheses***$p<0.01$, **$p<0.05$, *$p<0.1$

with self-selection correction. Tables 10 and 11 show that, in most cases, there are no large differences both between the two tables and when we compare these results with the estimates obtained from the full sample. Interestingly, the estimates reported in the last column of Table 11 (90th quantile) suggest that non-STEM graduates tend to benefit more from employment in research-oriented jobs as the wage associated with such jobs increases more than what occurs for STEM graduates. This can be probably related to the lower demand of research-oriented jobs in non-STEM disciplines in the Italian labor market (Ghosh & Grassi, 2020). These results emphasize contextual variation in the GWG and RO job returns across fields, though they do not fundamentally alter our core interpretation of the GWG in research careers.

Finally, we consider that PhDs' careers may follow two main routes, inside and outside academia. In Tables 12 and 13, the coefficients on the female dummy are smaller in magnitude within the academic sector, suggesting a narrower gender wage gap compared to other sectors. This finding aligns, at least partially, with Schulze (2015), who reports no significant gender wage gap within academia. In our sample, at the 10th percentile, the estimated coefficient is−0.083 in academic jobs and −0.139 in non-academic jobs. Also, the difference in estimated parameters is larger for increasing quantiles. This suggests that the gender pay gap tends to be lower when we move toward the lower tail of the wage distribution. Furthermore, we notice that there are significant differences in the RO job coefficients. While in academic jobs the larger impact on wages is observed at the 10th percentile, in non-academic jobs we see that the effect is larger at the 90th percentile. This suggests that while the private sector tends to reward PhD competencies mostly in the upper tail of the distribution, in the academic sector (which overlaps almost completely with the public sector) there is an upward flattening of wages. The observed differences between academic and non-academic sectors can largely be attributed to the distinct wage regulation mechanisms operating in each context. The academic sector, which overlaps almost completely with the public sector, operates under a highly regulated wage-setting framework characterized by standardized pay scales, collective bargaining agreements, and government regulations that govern public sector employment. This institutional structure inherently limits flexibility in individual wage negotiations and promotes more transparent, rule-based promotion and compensation systems. These regulatory mechanisms tend to compress wage distributions, creating smaller gaps between high and low earners and potentially reducing opportunities for gender-based wage discrimination to emerge or persist. However, while standardized pay scales may limit direct wage discrimination within

Table 8 RIF decomposition of log monthly wages with selection

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Male wages	7.053*** (0.005)	7.382*** (0.004)	7.881*** (0.009)
Female wages	6.826*** (0.016)	7.264*** (0.003)	7.659*** (0.008)
Gender pay gap	0.227*** (0.017)	0.118*** (0.005)	0.222*** (0.012)
Endowment effect			
RO job	0.044*** (0.008)	0.016*** (0.002)	0.032*** (0.004)
Selection	0.000 (0.002)	0.000 (0.001)	0.000 (0.002)
Selection squared	0.002 (0.002)	0.000 (0.000)	−0.002** (0.001)
Less than 30	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Not single	0.002 (0.002)	0.000 (0.000)	0.002** (0.001)
PhD on time	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Experience abroad during PhD	−0.000 (0.001)	0.001** (0.000)	0.003*** (0.001)
Field of study	0.068*** (0.009)	0.023*** (0.002)	0.027*** (0.006)
University ranking	0.006 (0.005)	0.001 (0.001)	0.001 (0.003)
Channel job	−0.013*** (0.004)	0.001*** (0.001)	0.007*** (0.002)
Ateneo FE	0.007 (0.006)	0.002 (0.001)	0.004 (0.004)
Cohort FE	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Total explained	0.116*** (0.012)	0.047*** (0.003)	0.075*** (0.007)
Coefficient effect			
RO job	−0.231*** (0.088)	0.019 (0.023)	−0.032 (0.054)
Selection	−0.000 (0.001)	0.000 (0.000)	−0.000 (0.000)
Selection squared	0.008 (0.014)	−0.001 (0.003)	0.000 (0.008)
Less than 30	0.010 (0.011)	0.002 (0.003)	0.002 (0.008)
Not single	0.056*** (0.017)	0.043*** (0.005)	0.054*** (0.012)
PhD on time	−0.036 (0.045)	−0.026** (0.012)	−0.029 (0.031)
Experience abroad during PhD	0.004 (0.014)	0.007* (0.004)	−0.002 (0.010)
Field of study	−0.028*** (0.008)	0.005* (0.003)	−0.012* (0.007)
University ranking	0.016 (0.020)	−0.002 (0.006)	0.015 (0.017)
Channel job	−0.118*** (0.045)	−0.069*** (0.010)	−0.064** (0.025)
Ateneo FE	0.101 (0.067)	0.02 (0.021)	0.079 (0.057)
Cohort FE	−0.000 (0.001)	−0.000 (0.000)	−0.001 (0.001)
Total unexplained	0.111*** (0.016)	0.072*** (0.005)	0.147*** (0.014)

Robust standard errors in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

the same positions, gendered differences may still emerge through differential patterns in career progression, with women potentially facing barriers in advancing to higher-paid positions or ranks within the academic hierarchy. In contrast, the non-academic sector operates primarily through market-driven wage determination processes, where individual negotiation, company-specific policies, and performance-based pay systems predominate. While this market-based approach offers greater flexibility in compensation decisions, it also creates more opportunities for subjective evaluation processes and potential bias to influence wage outcomes. The resulting wage distributions in the non-academic sector tend to be wider and more variable, reflecting both the greater rewards for high performance and

Table 9 UQR of log monthly wages with selection by cohorts

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
2004 cohort: N = 4104			
Female	−0.154*** (0.034)	−0.085*** (0.011)	−0.216*** (0.035)
RO job	0.425*** (0.117)	0.260*** (0.028)	0.541*** (0.098)
Selection	−0.161** (0.075)	−0.111*** (0.019)	−0.307*** (0.065)
Selection squared	−0.020 (0.037)	−0.015* (0.009)	0.043 (0.032)
2006 cohort: N = 5197			
Female	−0.095*** (0.020)	−0.077*** (0.009)	−0.152*** (0.031)
RO job	0.394*** (0.074)	0.161*** (0.027)	0.555*** (0.091)
Selection	−0.168*** (0.047)	−0.082*** (0.018)	−0.283*** (0.061)
Selection squared	−0.028 (0.023)	−0.003 (0.008)	0.048 (0.030)
2008 cohort: N = 4515			
Female	−0.107*** (0.028)	−0.095*** (0.011)	−0.160*** (0.024)
RO job	0.391*** (0.094)	0.303*** (0.031)	0.470*** (0.065)
Selection	−0.114* (0.060)	−0.103*** (0.021)	−0.201*** (0.044)
Selection squared	0.012 (0.029)	−0.015 (0.009)	0.028 (0.020)
2010 cohort: N = 4574			
Female	−0.093*** (0.025)	−0.079*** (0.008)	−0.111*** (0.021)
RO job	0.388*** (0.085)	0.200*** (0.023)	0.295*** (0.056)
Selection	−0.115** (0.055)	−0.088*** (0.016)	−0.149*** (0.037)
Selection squared	0.018 (0.025)	−0.011 (0.007)	−0.033** (0.015)

All estimations include university fixed effectsRobust standard errors in parentheses***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 10 UQR of log monthly wages with selection—STEM subsample

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Female	−0.081*** (0.010)	−0.087*** (0.006)	−0.122*** (0.015)
RO job	0.298*** (0.034)	0.226*** (0.017)	0.413*** (0.043)
Selection	−0.107*** (0.022)	−0.090*** (0.012)	−0.212*** (0.030)
Selection squared	−0.013 (0.010)	−0.008 (0.005)	−0.010 (0.013)
Observations	11,346	11,346	11,346
R-squared	0.092	0.175	0.097

Estimates include university and cohort FERobust standard errors in parentheses***$p<0.01$, **$p<0.05$, *$p<0.1$

the increased potential for disparities based on factors beyond productivity. Understanding these institutional differences is crucial for interpreting our findings and their policy implications.

Collectively, these subsample analyses confirm the robustness of our main findings while highlighting the varying contexts in which gender wage gaps are more pronounced or reduced.

Table 11 UQR of log monthly wages with selection—non-STEM subsample

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Female	−0.089*** (0.023)	−0.059*** (0.007)	−0.184*** (0.026)
RO job	0.275*** (0.072)	0.221*** (0.020)	0.481*** (0.070)
Selection	−0.116** (0.047)	−0.098*** (0.013)	−0.190*** (0.047)
Selection squared	0.004 (0.022)	−0.006 (0.006)	0.067*** (0.022)
Observations	7044	7044	7044
R-squared	0.072	0.165	0.096

Estimates include university and cohort FERobust standard errors in parentheses***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 12 UQR of log monthly wages with selection—academic job

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Female	−0.083*** (0.019)	−0.047*** (0.005)	−0.079*** (0.019)
RO job	0.863*** (0.144)	0.258*** (0.026)	0.380*** (0.079)
Selection	−0.301*** (0.066)	−0.105*** (0.014)	−0.135*** (0.049)
Selection squared	−0.030 (0.039)	−0.008 (0.007)	−0.004 (0.025)
Observations	7341	7341	7341
R-squared	0.117	0.212	0.198

Estimates include university and cohort FERobust standard errors in parentheses***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 13 UQR of log monthly wages with selection—non-academic job

	(1)	(2)	(3)
	10th percentile	50th percentile	90th percentile
Female	−0.139*** (0.015)	−0.113*** (0.007)	−0.206*** (0.017)
RO job	0.345*** (0.042)	0.305*** (0.018)	0.506*** (0.042)
Selection	−0.113*** (0.028)	−0.124*** (0.012)	−0.259*** (0.028)
Selection squared	0.001 (0.013)	−0.019*** (0.005)	−0.027** (0.013)
Observations	11,049	11,049	11,049
R-squared	0.097	0.241	0.118

Estimates include university and cohort FERobust standard errors in parentheses***$p<0.01$, **$p<0.05$, *$p<0.1$

Conclusions

This study has provided an in-depth examination of the GWG among PhD recipients in Italy, particularly focusing on the impact of research-oriented jobs. We have shown that while research-oriented employment provides a partial buffer—cutting the gap in the 90th percentile by roughly 50%—it does not eradicate it, chiefly because women are less likely to occupy such roles and because unexplained returns to characteristics remain strongly gendered. Thus, our findings confirm the persistence of a significant GWG across wage quantiles, echoing the conclusions drawn by Ferri, García-Pereiro, and Pace (2022) that the wage gap is present even among highly educated individuals. Also, the unexplained component of the GWG expands as we move up the wage distribution, suggesting either glass-ceiling discrimination or gender-specific bargaining returns. Despite the expectation that individuals with a PhD should face more wage equality in the labor market, our results indicate that women in research-oriented positions still face a wage penalty compared to their male counterparts, albeit less severe than in non-research roles. This aligns with the broader literature, such as the findings of Blau and Kahn (2017) and Wiswall and Zafar (2018), highlighting heterogeneities linked to the sectorial nature of the wage gap.

The findings of this study show that even the most highly educated women face structural disadvantages at career onset, and such early gaps may cumulate through path-dependent promotion trajectories. Because expectations about the returns to advanced qualifications are formed early, the perception (and reality) of lower pay can deter women from pursuing certain research careers or encourage exit to occupations with shorter or more predictable pay-off horizons, leading to the socially inefficient misallocation of high-skilled talent. Longitudinal evidence from economics departments, for example, reveals that women are significantly less likely to obtain tenure and take longer to reach it—even after accounting for publications, teaching, and institutional characteristics—thereby widening cumulative lifetime earnings gaps (Ginther & Kahn, 2004). Thus, it is imperative to call for policy interventions targeting gender wage disparities in research-oriented positions. Policies could include more transparent salary structures and explicit promotion criteria in research roles to ensure equality of rewards and a more balanced path in the gender composition of research-oriented positions. Also, mentorship programs, standardized evaluations, and systematic monitoring of gender differences in grant funding and promotion outcomes are imperative to arrest the cumulative process by which early-career wage gaps translate into long-run disparities. Outside academia, fiscal incentives such as tax-credit schemes to hire female PhD graduates into R&D positions could replicate the compression effect we observe within academic research jobs. In addition, academia's tenure-clock extensions for childcare (common in many EU countries) could be legislated for private-sector researchers. This would promote equality of opportunities also outside academia.

This study, while comprehensive, has limitations that must be acknowledged. The analysis is confined to the Italian context and may not be generalizable to other countries. Another limitation is that our dataset lacks information on career interruptions, preventing any direct test of how breaks affect wages. Future work should link survey data with social-security histories so that maternity, childcare, or other career gaps can be modeled explicitly. Doing so would shed light on whether the unexplained component we identify is partly driven by intermittent participation. Despite this constraint, our evidence underscores the urgency of policies that broaden female access to research careers and enforce transparent remuneration across sectors. Finally, comparative studies involving multiple countries could provide a broader perspective on the issue and help identify universal versus context-specific factors influencing the GWG.

Author contributions Emanuele Grassi conceptualized the study, developed the research methodology, conducted the data analysis, and interpretation. Marco Savioli developed the literature review and participated in the data analysis and interpretation. Both authors have read and approved the final version of the manuscript.

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Data Availability The data underlying this study are not publicly available due to confidentiality restrictions.

Declarations

Ethics approval and consent to participate Not applicable.

Competing interests The authors declare no competing interests.

References

Adsera, A. (2006). An economic analysis of the gap between desired and actual fertility: The case of Spain. *Review Of Economics Of The Household, 4*(1), 75–95.

Alfano, V., Cicatiello, L., Gaeta, G. L., & Pinto, M. (2021). The gender wage gap among Ph.D. holders: Evidence from Italy. *The B.E. Journal of Economic Analysis & Policy, 21*(3), 1107–1148.

Altonji, J. G., & Zhong, L. (2020). The labor market returns to advanced degrees. *Journal of Labor Economics, 39*(2), 303–360.

Balsmeier, B., & Pellens, M. (2016). How much does it cost to be a scientist? *The Journal of Technology Transfer, 41*(3), 469–505.

Bjerk, D. (2008). Glass ceilings or sticky floors? Statistical discrimination in a dynamic model of hiring and promotion. *The Economic Journal, 118*(530), 961–982.

Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal Of Economic Literature, 55*(3), 789–865.

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *The Journal of Human Resources,* 8(4), 436-455

Boyle, G. 2008. Pay peanuts and get monkeys? Evidence from academia, *The B.E. Journal of Economic Analysis & Policy*, vol. 8, no. 1

Carriero, R., Coda Zabetta, M., Geuna, A., & Tomatis, F. (2024). Investigating phds' early career occupational outcomes in Italy: Individual motivations, role of supervisor and gender differences. *Higher Education, 87*(5), 1375–1392.

Castagnetti, C., & Giorgetti, M. L. (2019). Understanding the gender wage-gap differential between the public and private sectors in Italy: A quantile approach. *Economic Modelling, 78*, 240–261.

Cook, C., Diamond, R., Hall, J. V., List, J. A., & Oyer, P. (2021). The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers. *The Review Of Economic Studies, 88*(5), 2210–2238.

Firpo, S., Fortin, N. M., & Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica, 77*(3), 953–973.

Firpo, S., Fortin, N., & Lemieux, T. (2018). Decomposing wage distributions using recentered influence function regressions. *Econometrics, 6*(2), Article 28.

Fortin, N., Lemieux, T., and Firpo, S. 2011. Decomposition methods in economics, pp. 1–102, in *Handbook of Labor Economics*, Elsevier

Francesconi, M., & Parey, M. (2018). Early gender gaps among university graduates. *European Economic Review, 109*, 63–82.

Ghosh, S., & Grassi, E. (2020). Overeducation and overskilling in the early careers of PhD graduates: Does international migration reduce labour market mismatch? *Papers in Regional Science, 99*(4), 915–944.

Ginther, D. K., & Kahn, S. (2004). Women in economics: Moving up or falling off the academic career ladder? *Journal Of Economic Perspectives, 18*(3), 193–214.

Gobillon, L., Meurs, D., & Roux, S. (2015). Estimating gender differences in access to jobs. *Journal of Labor Economics, 33*(2), 317–363.

Goldan, L. (2021). Explaining the gender pay gap among doctoral graduates: Analyses of the German labour market. *European Journal of Higher Education, 11*(2), 137–159.

Goldman, M., & Kaplan, D. M. (2018). Comparing distributions by multiple testing across quantiles or CDF values. *Journal Of Econometrics, 206*(1), 143–166.

Jiang, X. (2021). Women in STEM: Ability, preference, and value. *Labour Economics, 70*, 1–32.

Jones, M., & Kaya, E. (2022). The gender pay gap: What can we learn from Northern Ireland? *Oxford Economic Papers, 74*(1), 94–114.

Juhn, C., & McCue, K. (2017). Specialization then and now: Marriage, children, and the gender earnings gap across cohorts. *Journal Of Economic Perspectives, 31*(1), 183–204.

Lassibille, G. (2001). Earnings distribution among Spanish engineers: Research vs. non-research occupations. *Research Policy, 30*(4), 673–680.

Leysinger, C., Hasgall, A., and Peneoasu, A.-M. 2020. *Tracking the careers of doctorate holders: EUA-CDE Thematic Peer Group report*, European University Association

Lörz, M., & Mühleck, K. (2019). Gender differences in higher education from a life course perspective: Transitions and social inequality between enrolment and first post-doc position. *Higher Education, 77*, 381–402.

Nisticò, R. (2018). The effect of PhD funding on postdegree research career and publication productivity. *Oxford Bulletin of Economics and Statistics, 80*(5), 931–950.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review, 14*(3), 693–709.

Passaretta, G. and Triventi, M. 2021. Inequality at the top. The gender wage gap among the Italian educational elites: SocArXiv

Pető, R., & Reizer, B. (2021). Gender differences in the skill content of jobs. *Journal of Population Economics, 34*(3), 825–864.

Roach, M., & Sauermann, H. (2010). A taste for science? PhD scientists' academic orientation and self-selection into research careers in industry. *Research Policy, 39*(3), 422–434.

Sarrico, C. S. (2022). The expansion of doctoral education and the changing nature and purpose of the doctorate. *Higher Education, 84*(6), 1299–1315.

Schulze, U. (2015). The gender wage gap among PhDs in the UK. *Cambridge Journal of Economics, 39*(2), 599–629.

Webber, K. L., & Canché, M. G. (2015). Not equal for all: Gender and race differences in salary for doctoral degree recipients. *Research in Higher Education, 56*(7), 645–672.

Wilcox, V., & Forhad, M. A. R. (2023). Reverses in gender salary gaps among STEM faculty: Evidence from mean and quantile decompositions. *The B.E. Journal of Economic Analysis & Policy, 23*(4), 943–979.

Wiswall, M., & Zafar, B. (2018). Preference for the workplace, investment in human capital, and gender. *The Quarterly Journal of Economics, 133*(1), 457–507.