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The mediator effect of STEM education on the gender pay gap: a case study of early-career graduates at a Southern Italian university

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Abstract

Despite recent progress towards a more balanced work environment in terms of gender, the Gender Pay Gap is still a widespread relevant issue both from the economic and sociopolitical points of view. This paper focuses on Italy and uses AlmaLaurea survey data on University of Palermo graduates one year after graduation. The aim is to investigate the potential mediator role of the field of study (STEM vs non-STEM) in the Gender Pay Gap. In fact, the low participation of female students in STEM fields, known to be the most remunerative fields, could partially explain the difference in the average monthly salary of the graduates. In this paper, we adopt a causal mediation framework with Propensity Score Weighting to address selection bias due to the observational nature of the study. We then employ quantile regression to capture heterogeneity across the salary distribution. Results, on the one hand confirm the well-known discrimination in salary between males and females, suggesting that structural and cultural barriers persist, on the other hand highlight the mediation role of the degree type. STEM degrees seem to give a consistent salary premium, particularly in the lower and middle quantiles of the salary distribution, significantly mediating the salary advantage of men. These findings underscore the need for policies that both promote women's access and retention in STEM education and address broader institutional and cultural sources of salary inequality.

Keywords Gender pay gap · Causal mediation analysis · STEM education · Quantile regression

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1 Introduction

The Gender Pay Gap (GPG) has deep roots. It has been formally defined and analysed on a large scale only since the mid-20th century, thanks to systematic studies and the collection of more precise statistical data. Nowadays, GPG remains a central concern for labour-market policy and academic research (Blau and Kahn 2017; Fortin and Frey 2024). Despite substantial progress in gender equality legislation across Europe, differences in earnings between women and men persist across sectors, occupations, and career stages (Weichselbaumer and Winter-Ebmer 2005; European Institute for Gender Equality 2024). In Italy, recent policy initiatives, including the Strategic Sustainability Plan for 2024–2026 (Ministero degli Affari Esteri e della Cooperazione Internazionale 2025), explicitly target the reduction of gender-based salary disparities, highlighting the continued relevance of the issue for both economic performance and social inclusion. The salary disparity is the average difference in earnings between genders in the workforce, highlighting a critical aspect of gender inequality in the workplace. This disparity extends beyond pay discrimination and includes broader issues such as occupational segregation, career interruptions, institutional settings, and educational choices as key explanatory mechanisms (Goldin 1990; Alkadry and Tower 2006; Bishu and Alkadry 2017; Blau and Kahn 2017). Among these factors, participation in Science, Technology, Engineering, and Mathematics (STEM) fields has received increasing attention because STEM degrees are typically associated with higher employment rates and salary premiums (AlmaLaurea 2023; ISTAT 2025a). However, women remain under-represented in many STEM disciplines across Europe, and this imbalance may contribute to observed wage disparities even before individuals fully enter the labour market (Blackburn 2017; Petrenko and Cadil 2024).

In this paper, we aim to study the gender effect on the salaries of Italian graduates who find employment within one year after graduation, considering the influence of the different gender distribution in STEM (those who studied within the fields of Science, Technology, Engineering, and Mathematics). While previous studies have analysed gender differences in education or labour-market outcomes separately, fewer contributions explicitly model STEM participation as a mediating mechanism linking gender to earnings, particularly in the Italian context using micro-level graduate data (Blau and Kahn 2017; Blackburn 2017; Verdugo-Castro et al. 2022; Petrenko and Cadil 2024). Specifically, we analyse administrative survey data from graduates of the University of Palermo collected through the Almalaurea consortium. The availability of detailed individual-level information allows us to adopt a mediation framework in which gender represents the treatment, STEM degree the potential mediator, and salary the outcome. This approach enables us to distinguish between the direct effect of gender on earnings and the indirect effect operating through educational choices.

Our research interest arises from two considerations regarding the phenomenon, both in its quantitative and qualitative aspects.

1. Quantitative aspect: Despite recent progress towards a better gender balance, the GPG is still a relevant issue both from an economic and a sociopolitical perspective (Fortin and Frey 2024), also in Italy. In fact, one of the main goals of Italy's Strategic Sustainability Plan for 2024–2026 (Ministero degli Affari Esteri e della Cooperazione Internazionale 2025) concerns the GPG: "Reducing the salary disparity between women and men, at

all levels of employment, down to a 1% difference." According to the Italian National Institute of Statistics (ISTAT 2025a), in 2022 the gender gap in average hourly earnings in Italy stood at 5.6%. The GPG tends to widen in managerial roles, reaching a gap of 30.8% among the highest hourly salaries. A marked difference is also observed between economic sectors: in the privately controlled sector, the GPG is 15.9%, whereas in the publicly controlled sector it falls to 5.2% (Bellomo et al. 2025). In the European Union (EU), the principle of "equal pay for male and female workers for equal work or work of equal value" is one of the main pillars (art. 119) of the Treaty of Rome 1957 later integrated by the Treaty on the Functioning of the European Union 2007 and enriched by the Decree 1006/54/CE of the European Parliament and by the Italian Legislative Decree No.5/2010. There has been a reduction in the mean European difference from 15,8% in 2010 to 12,7% in 2022, but still in several countries, the GPG reflects structural inequalities due to sex, discrimination in the hiring process, unequal distribution of the non-paid work and cultural stereotypes that persist in time (Lahuerta et al. 2024). According to the International Labour Organisation's 2023 report (Ubenova 2023), women around the world earn on average just 51 cents for every dollar earned by men.
2. Qualitative aspect: Discrimination and stereotypes are factors that are hard to measure and difficult to eliminate. But the GPG does not stem uniquely from cultural roots; there are other factors such as socioeconomic status, macro-region of residence and workplace, degree, and field of study that can enhance this disparity. Following Ubenova (2023), the salary disparity is even more pronounced in low- and lower-middle-income countries, then in upper-middle- and high-income countries. According to ISTAT (2025a), in 2022 a man holding a university degree earned on average about €16,000 more than a woman with the same qualification.

In this view, this paper makes two main contributions: it provides new evidence on early-career gender wage disparities using detailed Italian graduate data, a context where aggregate indicators may mask structural inequalities, and it introduces a mediation perspective to the study of education-related gender pay differences, clarifying the role of STEM participation in shaping salary outcomes.

The paper is structured as follows. Section 2 reviews the theoretical and empirical literature on gender pay gaps, educational choices, and STEM participation, highlighting the research gap addressed by this study. Section 3 describes the methodology, in particular the mediation framework and the use of propensity score. In Sect. 4 the data and an exploratory analysis are presented. Section 5 presents the results, and Sect.6 the conclusions.

2 Theoretical background

2.1 Determinants of the gender pay gap

A robust body of economic and sociological literature attributes the GPG to a combination of factors, sometimes emphasizing economic and structural determinants and, at other times, those related to cultural stereotypes. Historical analyses, such as Goldin (1990) in the United States, and Weichselbaumer and Winter-Ebmer (2005)'s meta-analysis of international evidence (later updated by Olivetti and Petrongolo (2008), have highlighted the roles of structural factors, institutional frameworks, and policy regimes in shaping salary inequality. Foundational work prior to the pandemic had already begun to map the contours of the GPG: Bishu and Alkadry (2017) conducted a systematic review of the GPG and its predictors, focusing on differences between public and private sectors, while Blau and Kahn (2017) examined its magnitude, trends over time, and underlying explanations, noting that gender differences in occupations and industries continue to contribute significantly, while differences in psychological or non-cognitive skills explain only a portion of the gap. After the COVID-19 pandemic, scholarly interest in the GPG was renewed, as the crisis exposed and intensified pre-existing disparities in economic participation and educational attainment (Giambalvo and Palumbo 2021) Occupational outcomes for women compared to young men play a central role: women are disproportionately employed in relatively low-paying sectors such as care, health, and education (contributing roughly 24% of the EU's overall pay gap) and are more likely to interrupt their careers for family and care-giving responsibilities, particularly in contexts such as Italy, where these duties fall predominantly on women (European Institute for Gender Equality 2024). Cultural and social factors, including gender stereotypes, influence women's educational and professional choices, as well as social norms that assign greater domestic and caregiving responsibilities to women (Dasgupta and Stout 2014; Kang et al. 2019; Stewart-Williams and Halsey 2021). Women are also more influenced by family expectations and social pressures, which may limit their professional opportunities relative to men (McCoy et al. 2022; De Gioannis 2025). Studies by Krause (2017) and Sloane et al. (2021) show that these patterns are particularly pronounced among young female graduates.

2.2 Gender differences in STEM participation

The under-representation of women in STEM fields has been widely documented across countries and institutional contexts (Blackburn 2017; Petrenko and Cadil 2024). Verdugo-Castro et al. (2022) analysed over 100 articles on the gender gap in higher STEM education, examining case studies and methods used mainly in European countries to quantify and reduce the phenomenon. Their analyses confirm that both economic and cultural factors also affect young female graduates: psychological factors, such as lower self-confidence in mathematical and scientific abilities, have been linked to women's lower participation in STEM, leading to underrepresentation in high-income sectors (Diekman et al. 2015). The methods used are predominantly econometric models applied to large datasets of employed workers, either at the country level or within specific sectors (large industries, small and medium-sized enterprises, type of contract, etc.) (Blau and Kahn 2017; Sassler et al. 2017; Stewart-Williams and Halsey 2021). Among STEM graduates, the female employment rate in Sciences and Mathematics is eight percentage points below that of men, while in Computer Science, Engineering, and Architecture, the gap widens to nine percentage points (ISTAT 2025a). Overall, ISTAT (2025a) reports that the employment rate for graduates aged 25–64 in technical-scientific disciplines is 86%, substantially higher than the 77.7% rate observed among graduates in the humanities. These figures suggest that educational pathway choices play a crucial role in shaping gender inequalities in occupational status, career trajectories, and salary levels. The AlmaLaurea Consortium, in its survey of the 2019 cohort of graduates interviewed five years after graduation, emphasizes that field-of-study choices are a key factor contributing to the GPG in high-income sectors with the greatest career prospects. Graduates in STEM fields report an average net monthly salary of €1,571, whereas graduates in non-STEM fields earn €1,350 on average (AlmaLaurea 2023), implying that holding a STEM degree confers a 16.4% salary premium. These findings indicate that women's underrepresentation in STEM not only affects employment probabilities but also translates into substantial differences in earnings, highlighting the interplay of structural, cultural, and educational factors in shaping the Italian GPG.

2.3 The gender pay gap in Italy

In Italy, numerous studies have quantified the GPG within the European context (Redmond and McGuinness 2019; Castellano and Rocca 2020). Zizza (2013) estimates the gender wage gap in Italy, accounting for two key features of the economy: the low rate of women's labour market participation and the high share of self-employment, using the Bank of Italy's survey on household income and wealth. The wage gap was found to increase over time, partly due to different policies regarding bonuses (performance-based pay) adopted by firms. Often the papers links the phenomenon to the structure of the Italian labour market (Barbieri et al. 2015; Petrenko and Cadil 2024). The Italian labour market is strongly characterized by gender- and education-related differences in entry and career development, as well as by a substantial employment gap disadvantaging women.

According to Encinas-Martín and Cherian (2023), in Italy pay discrimination is lower among highly educated groups due to a form of 'self-selection,' whereby only the most highly educated or skilled women enter paid work. Addabbo et al. (2007) argue that there is a positive correlation between pay, labour market discrimination, and levels of general and specific human capital (e.g., experience and tenure). Later, in 2011, the same authors analysed wage differentials in Italy by combining gender and education perspectives. They show, among other findings, that highly educated women possess better characteristics than highly educated men, which partially compensates for the relatively high difference in returns, particularly at the extremes of the distribution. Ferri et al. (2023) focus on graduates who are new to the labour market or who combine low levels of experience with high levels of education. Their results indicate that the GPG is already present at the very beginning of graduates' careers and increases when accounting for women's lower level of labour market participation. In a recent study, Meoli et al. (2024) investigate the effect of selected characteristics of recent STEM graduates on the difference between women and men in their likelihood of obtaining STEM occupations shortly after graduation. They find that students' graduation grades increase the probability of securing STEM occupations for both women and men.

Considering the evidence from economic and sociological literature in the specific context of the Italian labour market, the study aims to confirm the theses of Ferri et al. (2023) and Meoli et al. (2024). Specifically, this paper analyses the GPG among young graduates by field of study using a method to assess the relationship between income and gender, while attempting to account for confounding factors and spurious correlations with other socio-demographic and curricular covariates.

The method, new for application in this context, combined with data on graduates from a university located in an area with low employment rates (for both men and women) and a high propensity for student and worker mobility, provides an opportunity to contribute to the extensive literature on the GPG.

3 Methodology

To measure the causal mediating effect of a STEM degree on the GPG among graduates of the University of Palermo, we perform a causal mediation analysis within the potential outcomes framework. Our dataset comes from a cross-sectional observational study. The treatment variable is Sex,[1] for which assignment is a non-manipulable status, our outcome is the salary, and being graduated in a STEM field is assumed to be our mediator. Given that the treatment assignment is not random, and independence between treatment, outcome, and mediator cannot be guaranteed, we adopt a Propensity Score Weighting (PSW) approach, which aims to remove the differences in the treatment groups not attributable to the treatment. In our case, the set of observed covariates is sufficiently rich for the intended adjustment (see Sect. 4 for the complete list). Our PSW approach uses Overlap Weights (OW) (Zhou et al. 2020), which optimise the efficiency of comparisons between treatment groups (Li et al. 2018). The weights are used both in the model for the mediator and the outcome. For the mediator, we use a probit model; for the outcome, we use a quantile regression model to capture the heterogeneity of the treatment and mediator effect across different quantiles of Y (salary) (Bind et al. 2017). Finally, we estimate the Quantile Causal Mediation Effect (QCME), which represents the portion of the total GPG mediated by obtaining a STEM degree, and the Quantile Direct Effect (QDE), which represents the portion of the gender effect on the outcome not mediated by STEM.

3.1 Mediation analysis and counterfactual framework

Following Imai et al. (2010), we adopt the Potential Outcome framework, under the Sequential Ignorability Assumption. This guarantees that the average effects of causal mediators are identified in a non-parametric way. In particular, it avoids restrictive assumptions on functional forms or distributions. This approach offers flexible estimation procedures that adapt to a wide range of situations.

Formally, let $T_i \in \{0, 1\}$ denote the treatment status for unit *i* (e.g. gender with $T_i = 1$ for male and $T_i = 0$ for female). Let $M_i(t)$ denote the potential mediator value for unit *i* under the treatment $T_i = t$. Similarly, let $Y_i(t, m)$ represent the potential outcome (salary) for unit *i* under treatment *t* and mediator *m*. Under this notation, the total treatment effect for unit *i* is defined as:

$$\tau_i = Y_i(1, M_i(1)) - Y_i(0, M_i(0)) \tag{1}$$

The total effect can then be decomposed into two parts. First, the causal mediation effect (indirect effect) is expressed as:

$$\delta_i(t) = Y_i(t, M_i(1)) - Y_i(t, M_i(0)), \quad t = 0, 1 \tag{2}$$

This represents the difference between the potential outcome that would be obtained with treatment status *t* and the potential outcome that would be obtained if the treatment status

[1] In this paper, we consider the GPG as a measure of the salary discrepancy between males and female, and the Sex as the variable used in our model indicating the status of “male” or “female” as collected administratively.

were the same but the mediator took a value that would be obtained with the other treatment status. Note that only one status is observable, while the other represents the counterfactual. Therefore, if $t = 0$, $Y_i(0, M_i(0))$ is observed and $Y_i(0, M_i(1))$ is counterfactual and when $t = 1$, the term $Y_i(1, M_i(1))$ is observed and $Y_i(1, M_i(0))$ is counterfactual (Chi et al. 2022).

$\delta_i(0)$ is usually termed as the *pure indirect effect* and in our paper it compares female graduates' observed salaries with a hypothetical scenario in which their STEM degree attainment mirrors male graduates. $\delta_i(1)$ is referred to as the *total indirect effect* and in our case it compares observed salaries of male graduates with the scenario where their STEM attainment aligns with female graduates.

The direct effect, capturing all other causal mechanisms, is defined as:

$$\zeta_i(t) = Y_i(1, M_i(t)) - Y_i(0, M_i(t)), \quad t = 0, 1 \tag{3}$$

In other words, $\zeta_i(t)$ is the direct effect of the treatment when the mediator is held constant at the level corresponding to treatment status (Imai et al. 2010). In our example, $\zeta_i(1)$ represents the direct effect of the gender on graduate i's salary level while holding the STEM degree constant at the level that would be realised under the *t* gender status. Although $Y_i(t, M_i(t))$ is observable for units with $T_i = t$, $Y_i(t, M_i(1-t))$ can never be observed for any unit. Since individual-level causal effects are unobservable, researchers focus on the identification and estimation of the average causal effect (Imai et al. 2010; Chi et al. 2022). The expected values, $\mathbb{E}(\delta_i(t))$ and $\mathbb{E}(\zeta_i(t))$ are the Average Causal Mediation Effect (ACME) and the Average Direct Effect estimated adopting mean regression models.

Identification of the ACME requires the Sequential Ignorability assumption (Imai et al. 2010), which consists of two assumptions (Carreras 2019):

1. Treatment Ignorability:

$$T \perp (Y(0), Y(1), M(0), M(1)) \mid X \tag{4}$$

   In other words, conditional on the observed pretreatment covariates *X*, the treatment *T* is independent of all potential values of the outcome *Y* and mediating variables *M*.
2. Mediator Ignorability:

$$M \perp Y(T) \mid (T, X) \tag{5}$$

   In other words: the observed mediator *M* is independent of all potential outcomes *Y*(*T*) given the observed treatment *T* and pretreatment covariates *X*. The assumption ensures no unmeasured confounding exists in the treatment-mediator and mediator-outcome relationships.

Note that in observational studies or in cases where treatment assignment is not manipulable (e.g., sex, race), the assumption of Treatment Ignorability is generally not valid (Imai et al. 2010; Zhou et al. 2020). In such situations, several methods have been proposed to balance pre-treatment variables between the treatment groups. Since our treatment variable is sex, which is not manipulable and is correlated with STEM and salary, we propose the use of

PSW to address this problem, as described in detail in following Sect. 3.2. This approach allows us to approximate a pseudo-randomised setting in which treatment assignment can be assumed to be ignorable. However, sequential ignorability also requires mediator ignorability, given treatment and pre-treatment covariates. This assumption implies that, conditional on sex and observed pre-treatment characteristics, there are no unobserved confounders of the relationship between field of study (STEM vs. non-STEM) and salary. Importantly, this assumption may fail even in randomized experiments, since the mediator is typically not randomly assigned (Imai et al. 2010). To mitigate the risk of omitted variable bias in the mediator-outcome relationship, we repeated the analysis including a richer set of pre-treatment covariates, such as high-school background and high school grades, motivations behind the choice of degree programme, parental education, and social class. The overall pattern of results remains almost unchanged with this richer specification, indicating that the estimated mediation effects are robust to a larger set of observed confounders. Thus, we present only the results of our reduced model. Nevertheless, our causal interpretation relies on the sequential ignorability assumption. Accordingly, the estimated quantile mediation effects should be interpreted within a causal mediation framework only under this identifying assumption.

3.2 Propensity score weighting

In causal analysis randomised experiments are generally considered the gold standard for estimating causal effects. Numerous statistical methods have been developed to correct problems, such as selection bias, in both non-randomised experimental and observational studies (Rubin 1997; Imai et al. 2010; Hu and Mustillo 2016). Our dataset comes from a cross-sectional observational study in which random assignment to the treatment variable (Sex) is not possible and the risk of selection bias becomes relevant. For instance, unobserved factors like personal life aims, preferences, risk aversion, and networks may affect both field choice and earnings (Xie 2006). As a result, the observed salary differences between males and females may reflect confounding factors rather than the true effect of gender. In such non-randomised settings Propensity Score (PS) methods are widely used to reduce confounding when estimating treatment effects. Under certain assumptions, PS-based adjustments allow researchers to emulate some aspects of a randomised design and obtain unbiased estimates of causal effects (Rubin 1997; Rosenbaum and Rubin 1983). There exist various ways of using PS. In this paper, we apply PS weighted (PSW) methods to achieve a balance of covariates between the treatment (male) and control (female) groups (Hu and Mustillo 2016). The key idea is to use PSW to construct a pseudo-population in which the distributions of covariates are balanced between treatment groups (Zhou et al. 2020).

While the inverse probability weighting (IPW) is the most commonly used method among the balancing weights, it is highly sensitive to extreme PS values, leading to extreme weight values, inflated variances and biased estimates of the treatment effect (Zhou et al. 2020). To overcome these limitations, alternative balancing weights such as OW or Entropy Weights have been proposed in the literature (Zhou et al. 2020). Notably, OW focuses on the subpopulation with the greatest covariate overlap between groups, weighting each unit proportional to its probability of assignment to the opposite group (Li et al. 2018). Unlike

IPW, OW produce weights bounded between 0 and 1, mitigating the influence of extreme PS values and producing a better balance across covariates.

Formally, the PS is defined as:

$$e(\mathbf{X_i}) = P(T_i = 1|\mathbf{X_i}) \tag{6}$$

and it is typically estimated using logistic regression. OW are calculated as:

$$w_i = \begin{cases} 1 - e(\mathrm{X}_i) & \text{if } T_i = 1 \\ e(\mathrm{X}_i) & \text{if } T_i = 0 \end{cases} \tag{7}$$

Two diagnostic checks are performed:

1. Assessment of overlap (positivity hypothesis) in the distributions of PS between groups to identify their common support.
2. Balance of covariates before and after weighting, ensuring comparability of the treated and control groups in terms of observed covariates.

3.3 Quantile causal mediation analysis

We are interested in assessing the differential mediation impact of obtaining a STEM degree on different salary levels and not just on the average; average estimates may not reflect effects that occur primarily in the tails of the outcome distributions (Bind et al. 2017). The Quantile Regression approach allows us to model conditional quantiles of the outcome distribution, rather than just the mean. It achieves this by weighting positive and negative residuals asymmetrically, which shifts the fitted regression function toward a specified quantile (e.g., the median, quartiles, or other percentiles) of the conditional distribution (Koenker 2005). In our context, this approach is particularly relevant in light of the unequal effects often observed between treatment, mediator and outcome at different quantiles of the salary distribution (Shen et al. 2014; Bind et al. 2017). Furthermore, quantile regression is more robust to outliers and non-linear outcome distribution, which is generally the case with right-skewed salary data.

Therefore, we estimate: i) the QCME, which represent the difference between a given quantile (e.g., the median) of two potentially relevant outcomes; ii) the QDE that measures how a treatment or exposure shifts a specific quantile of the outcome distribution, holding constant the mediator(s), rather than its average (Imai et al. 2010).

Under the Sequential Ignorability Assumption, QCME and QDE are estimated via two weighted regression models, one for the mediator:

$$E(M_i|T_i, \mathrm{X}_i) = \gamma_0 + \gamma_1 T_i + \mathrm{X}_i\gamma_2, \tag{8}$$

and one for the outcome:

$$Q_\tau(Y_i|T_i, M_i, \mathrm{X}'_i) = \beta_0(\tau) + \beta_1(\tau)M_i + \beta_2(\tau)T_i + \beta_3(\tau)(M_i \times T_i) + \mathrm{X}'_i\delta(\tau) \tag{9}$$

where X_i, $\mathbf{X}'_i$ are $n \times k_1$ and $n \times k_2$ matrices of covariates not necessarily disjoint.

Following Huang et al. (2015), the weighted quantile regression estimators for τ_{th} quantile, $\boldsymbol{\theta}(\tau) = \left(\beta_0(\tau), \beta_1(\tau), \beta_2(\tau), \beta_3(\tau), \boldsymbol{\delta}(\tau)\right)^\top \in \mathbb{R}^{k_2+4}$ is obtained by

$$\hat{\boldsymbol{\theta}}_w(\tau) = \arg \min_{\boldsymbol{\theta} \in \mathbb{R}^{k_2+4}} \sum_{i=1}^{n} w_i \, \rho_\tau\big(Y_i - \theta \mathrm{Z}_i\big), \tag{10}$$

where $\mathrm{Z}_i = \left(1,\, \hat{M}_i,\, T_i,\, \hat{M}_i T_i,\, \mathrm{X}_i'\right)^\top \in \mathbb{R}^{k_2+4}$ and w_i refers, in our case, to the OW defined in (7) and

$$\rho_\tau(u) = u\big(\tau - I(u < 0)\big) = \begin{cases} u(\tau - 1), & u < 0 \\ u\tau, & u \geq 0 \end{cases} \tag{11}$$

where $\rho_\tau(u)$ represents the loss function used in quantile regression.

The non-parametric identification allows the counterfactual framework to be extended to quantile regression models. For these models, uncertainty estimates are calculated using non-parametric bootstrapping that allow to obtain a distribution of causal mediation effects (Imai et al. 2010). In addition, we relax the non-interaction assumption and assume that the role of the mediator in influencing the outcome differs based on the treatment status (Chi et al. 2022). Given the dependence of causal mediation effect on the treatment condition, we separately estimate QCME(0) and QCME(1), which measure mediation effects among treated (males) and control (females), respectively (Chi et al. 2022). QCME(1) represents the τ quantile difference between two outcomes associated with male graduates: (a) their observed salary and (b) the salary level they would have if they were male, but with the STEM level they would have if they had been assigned to the female group. While QCME(0) denotes the difference between two outcomes for female graduates: (a) their salary levels when they remain in the female group, but their STEM levels are those they would have if they were assigned to the male group, and (b) their observed salary level (Chi et al. 2022). The analysis was carried out in R using the `mediation` library (Tingley et al. 2014) and the `quantreg` library (Koenker et al. 2018).

4 Data

The data used in this analysis were provided by AlmaLaurea, a consortium of Italian universities that collects and analyses data on graduates' educational and occupational outcomes. The Italian Ministry of University and Research supervises it. Among its main objectives is monitoring and evaluating the university system by gathering detailed information on students' academic careers, socio-demographic backgrounds, and employment outcomes. The AlmaLaurea system is based on two key surveys: i) the Graduates' Profile Survey, which captures students' characteristics at graduation (e.g., final academic performance, mobility, university path opinion, socio-economic background); 2) the Graduates' Employment Status Survey, conducted 1, 3, and 5 years after graduation, which assesses job placement, contract type, net monthly income, job satisfaction, and skill alignment. For privacy reasons, as reported in Sect. 1, we have access only to AlmaLaurea data of the University of Palermo (Italy). The whole original database consisted in 14699 records and about a hundred variables, regarding all the graduates at the University of Palermo who completed a Master's or single-cycle degree between 2014 and 2021, interviewed one year post-graduation. Table 1 focuses on the distribution of the graduates by Field of Study, Sex, and Employing Status. Among the non-STEM graduates, the non-employed group prevails (52.76 vs. 47.24%), whereas among STEM graduates the employed group is by far larger than the non-employed group (66.86 vs. 33.14%). Furthermore, although the population examined consists predominantly of women, the percentage of women employed in STEM is lower than that of men employed in STEM (66.86 vs. 78.08%). This result is mainly attributable to the well-known difficulties women face in entering the job market (Andreotti et al. 2013), a situation that is further amplified by the territorial context (Southern Italy), which is characterized by a local job market that is significantly more active and dynamic for the male workforce (ISTAT 2025b).

Table 2 provides an overview of the students' characteristics considered for the analysis, with respect to the subset of occupied graduates. The selected and used subset consist on 4068 records because it is without any missing data. Since the distributions of the respondents' main characteristics appear to be relatively stable across the different survey years, we chose to pool the data from all years. This allowed us to work with a larger dataset without compromising the comparability of the information over time. We are supported in this as a preliminary analysis on the salary distribution over time did not show any presence of shocks but, on the contrary, a natural increasing trend over time of the median wage (Fig. 1).

The following comments go into the merits of the most relevant evidences; where no gender differences emerge, the data will not be commented on. The data are majority Female (57%). STEM degrees account for approximately one-third of the data, though a significant gender disparity emerges: Males are 3.5 times more likely to be STEM graduated than Females. This result highlights the persistent gender segregation in academic specialisation, which in turn has implications for labour market outcomes, as STEM qualifications are often associated with higher remuneration and access to technical or high-skilled occupations.

Motivational factors for degree choice lean towards a balance between cultural and professional aspirations, with 57% reporting a combination of both. Notably, a non-negligible 12% of respondents selected their field for neither cultural nor professional reasons, warranting further investigation into potentially structural or opportunistic influences on educational choices.

Parental education reveals modest levels of tertiary attainment: only 20% of fathers and 18% of mothers hold a Degree or higher qualification (representing together the 11% of the whole data). Table 3 highlight a noteworthy proportion of graduates (about 1 in 4) coming from families where neither parent progressed beyond Middle School. These distributions may reflect intergenerational patterns in educational attainment and contribute to social class reproduction, particularly when combined with the self-reported class indicators.

Table 1 Distribution of graduates by employing status, field of study, and sex

Field of study							
	Non-STEM			STEM			
Employing status	Sex			Sex			
	Female	Male	Total	Female	Male	Total	Total
Employed	3755	1613	5368	803	1909	2712	8080
Non-employed	4194	1491	5685	398	536	934	6619
Total	7949	3104	11053	1201	2445	3646	14699

Table 2 Descriptive statistics

Variable	Categories	Sex: Female (2332)	Male (1736)	Total (4068)
Degree use	Neither required nor useful	308	162	470
	Not required but useful	695	532	1227
	Legally required but not necessary	398	486	884
	Legally required	931	556	1487
Education of father	Until middle school	886	534	1420
	Job qualification	76	72	148
	High school	948	746	1694
	Degree (at least)	422	384	806
Education of mother	Until middle school	830	541	1371
	Job qualification	50	34	84
	High school	1064	805	1869
	Degree (at least)	388	356	744
Field of study	Non-STEM	1952	737	2689
	STEM	380	999	1379
High school type	Humanistic	1307	303	1610
	Scientific	809	989	1798
	Technical college	216	444	660
Job required skills	Elementary	508	260	768
	Intermediate	1216	703	1919
	High	608	773	1381
Motivational factors	More cultural	558	359	917
	More professional	165	164	329
	Cultural & Professional	1284	1019	2303
	Neither/Nor	325	194	519
Social class	Working class	610	435	1045
	Self-employed middle class	490	318	808
	Middle class	855	667	1522
	Upper-class	377	316	693
Working jobsite	South	1627	942	2569
	Centre	109	94	203
	North	532	641	1173
	Abroad	64	59	123
Working sector	Private/Non-profit	1762	1463	3225
	Public	570	273	843
High school Diploma grade	(mean)	84.54	82.40	83.63
Final degree mark	(mean)	109.78	109.75	109.76
Salary (Euro)	(mean)	1052.86	1320.33	1167.00

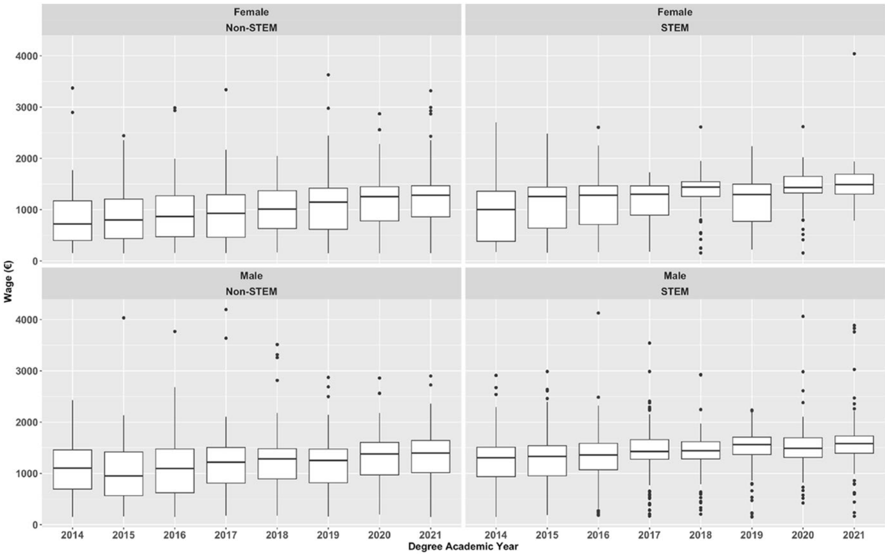

Fig. 1 Monthly wage (in Euros) by sex and field of study, per degree academic year

Table 3 Contingency table between father's and mother's education level

Father education level	Mother education level				Total
	Until middle school	Job qualification	High school	Degree (at least)	
Until middle school	940	26	409	45	1420
Job qualification	55	19	60	14	148
High school	337	33	1067	257	1694
Degree (at least)	39	6	333	428	806
Total	1371	84	1869	744	4068

Social class self-identification highlights a diverse socioeconomic background: 37% of respondents identify with the middle class, 26% with the working class, and 20% with the self-employed middle class. Only 17% consider themselves upper-class, reinforcing that higher education in this data continues to serve as a mechanism of social mobility for a broad population.

High School background is evenly distributed between Scientific (44%) and Humanistic (40%) tracks, with Technical colleges comprising the remaining 16%. This balance likely mirrors the Italian upper secondary school system, though the higher proportion of scientific backgrounds may have implications for access to and success in STEM pathways. But if we consider the distinction by Sex, it reflects the national cultural tradition (ISTAT 2021) that counts Females in greater presence in the Humanities (3 times more than Males) and Males in greater presence in the Scientific and Technical schools (1.9 times more than Females).

Regarding job requirements and skills, only 37% are in positions where a degree is required by law, and 12% report their degree to be neither needed nor useful for their current job. This mismatch may point to structural inefficiencies in the labour market or a broader phenomenon of over-education. Job required skills are skewed towards intermediate-level roles (47%), with high-skilled positions accounting for only one-third. Controlling for Sex, the greatest gap is found for jobs requiring High Skills: almost twice as many Males as Females declare that their job requires high skill (44.5 vs. 26.07%). As for Intermediate Skills, the gender difference is small: these skills are declared by 52% of Females versus 40.5% of Males. This result could be interpreted in two ways: i) Males are preferred to Females when a High Skill Job is required, while Females are preferred in the case of an Intermediate Skill one; ii) the data reflects the different perception that Males and Females may have when comparing their own skills with those required by the job position, overestimating or underestimating them.

Most graduates remain working in the South (63%) or, at most, move to the North (29%). Considering the gender distinction, it is interesting to note that there is a higher probability of staying in the South for Females than for Males (Relative Risk = 1.29), whereas the opposite holds for the North (Relative Risk = 0.59). This could also be a first indication of the wage gap, as salaries in the North of Italy have historically been higher than those in the South (Daniele 2022).

The public sector employs 21% of graduates, with the remaining 79% working in the private or non-profit sectors. Academic performance indicators (Table 2), i.e. mean high school grade (83.6/100) and final degree mark (109.8/110), suggest a relatively high-achieving students, while the average monthly salary stands at approximately €1167.

Focusing on (self-declared) salary, we also considered the relationships among monthly net salary, High School Grade, and Final Diploma Mark. The correlation coefficients are statistically significant but small in magnitude (Table 4). Findings suggest that school and university performance have a limited direct influence on salaries one year after graduation. This is consistent with labour market scientific literature (Stokke 2021) showing that in early career stages, salaries are shaped more by field of study, gender, sector of employment, and social capital than by individual academic success alone. The rough difference in Salary between Females and Males start to emerge here, and it is the subject of this study: a significant difference in declared income between Males and Females, with an average difference of about 300 euros in favour of the former.

The boxplots in Fig. 2 illustrate the distribution of monthly salaries, offering a picture of how earnings vary according to Sex, STEM, their interaction, Work Sector and Job Required Skills. The boxplots reveal substantial heterogeneity in salary distributions, with many high-end outliers indicating the presence of particularly well-paid positions, especially among Males, STEM graduates, and High-skilled workers. Going deeper, data clearly shows the presence of a gender salary gap: Male graduates tend to earn more than Female ones in terms of median and average salaries. This gap persists even when controlling for Field of Study, suggesting differences in how education pays off or how the job market works dif-

Table 4 Correlation matrix among salary, high school diploma grade, and final degree mark

	Salary	High school diploma grade	Final degree mark
Salary	1.000	0.0312***	0.0194**
High school diploma grade		1.000	0.1970***
Final degree mark			1.000

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

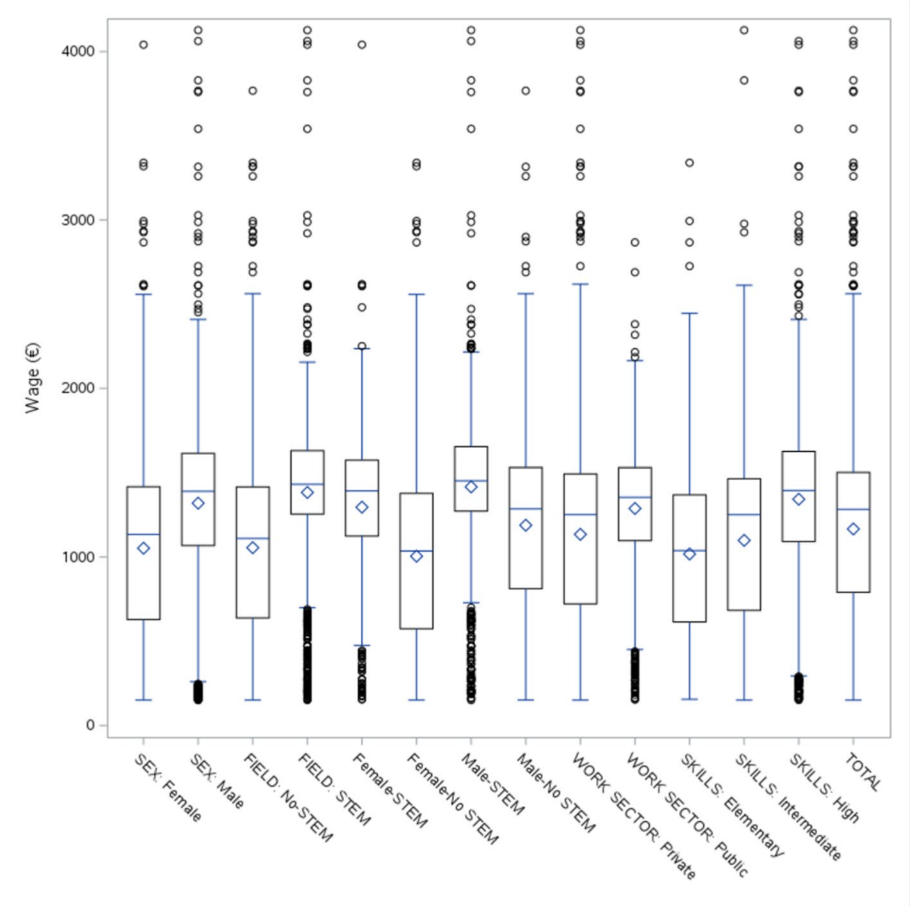

Fig. 2 Distribution of salary (€) by sex, field of study, their interaction, work sector, job required skills, and marginally (mean in diamond mark)

ferently for men and women. Working Sector also seems to influence salaries, with workers in the Public sector showing slightly higher median salaries than those in the Private sector. However, the differences are lower than those observed for Sex or Field of Study. Finally, salary levels seem to be strongly associated with Job Required Skill level: individuals with High skills receive the highest salaries, followed by those with Intermediate and Elementary skills. The dispersion of salaries is also greater among High-skilled individuals, suggesting a more heterogeneous set of roles and pay scales in this group.

Final considerations about salary and other variables can take into account the interaction of Work Sector, Job Required Skills and Sex (Table 5). Across all categories, Males consistently earn more than Females, regardless of the sector or the skill level of the job. The most remarkable finding in the Private/Non-profit sector is the significantly larger gap for Intermediate-level jobs, suggesting possible issues related to promotion, job type, or negotiation power in mid-level roles. Compared to the Private sector, the GPG in the Public sector is generally less extreme and more uniform across different job levels. While Males

Table 5 Salary statistics by work sector, job required skills, and sex

Work sector	Job required skills	Sex	Monthly-salary (€)	
			Mean	Std dev
Private/Non-profit	Elementary	Female	882.79	494.75
		Male	1100.30	451.77
	Intermediate	Female	864.64	494.09
		Male	1249.99	502.42
	High	Female	1262.55	477.29
		Male	1402.64	509.24
Public	Elementary	Female	1250.24	476.38
		Male	1445.25	345.64
	Intermediate	Female	1222.91	396.15
		Male	1384.52	384.41
	High	Female	1245.01	560.68
		Male	1494.83	453.44

still earn more than Females in every category, the differences in the Public sector tend to be smaller in size and relatively similar across skill levels, whereas in the Private sector, the gap varies more considerably, particularly in Intermediate-level jobs. The public sector, despite being more regulated by law, still displays a consistent gap, mostly in High-Skilled jobs. This disparity is unlikely to stem from direct salary discrimination and is more likely attributed to a set of structural and contextual factors. Firstly, men may be more likely to access higher-paying public roles, either by succeeding in more competitive recruitment processes or entering sectors with additional allowances (such as shift work, remote areas, or managerial responsibilities). Secondly, there may be differences in contract types: while both genders are often employed on temporary or atypical contracts in the early career stage, women might be overrepresented in less remunerative arrangements, such as internships or lower-grade fixed-term roles. In addition, part-time employment may also play a role, with some young women opting for or being channelled into reduced working hours, which directly impacts monthly earnings.

Finally, another aspect to consider could be the type of work performed, as the contractual salary varies significantly between STEM-related jobs and those in other fields (AlmaLaurea 2025). Unfortunately, the available data does not allow us to obtain this detail.

5 Results

This section shows the results of the PSW procedure and the causal mediation analysis. The propensity score model and balance diagnostics are presented first, followed by the quantile mediation results.

Figure 3 shows the distribution of the PS for the two groups; then the results of covariate balance are shown in Fig. 4. The PS model was based on a logistic regression, including student educational and social background variables (Table 2). The distribution of estimated PS (Fig. 3) for males (treatment) and females (control) reveals a moderate overlap. Specifically, females show a concentration of scores in the low range of the distribution (approximately 0.1–0.3), while males show a peak in the high range (approximately 0.6–0.8). The common

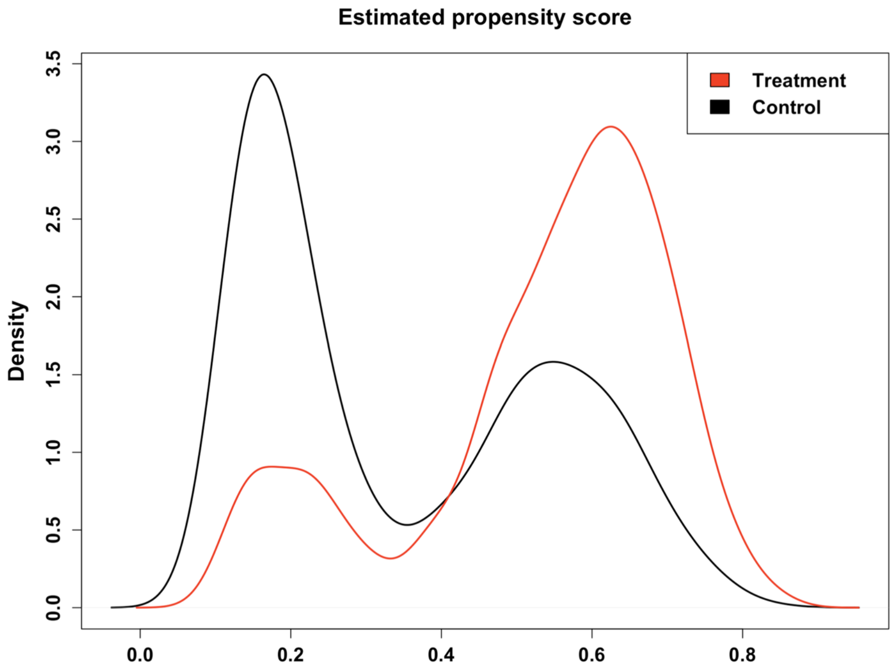

Fig. 3 Density plot: distribution of overlap weight for treated and control group

support is found between 0.4 and 0.6, indicating that outside this range, many observations have almost no counterpart in the opposite group.

The PS procedure using OW effectively improved the balance of covariates between male and female graduates in our data (Fig. 4). Before weighting, there were substantial differences in terms of school of origin and high school grade. After applying OW, these differences were minimised, as demonstrated by the covariate balance diagnostics in Fig. 4, which indicates a good balance between the two groups, now comparable in terms of observed characteristics.

Table 6 presents the estimates of the weighted probit regression for the mediator variable STEM. As expected, males show a higher propensity to enrol in STEM compared to females ($\hat{\beta} = 1.08$). The high school type remains the strongest predictor in explaining the choice of a STEM course, especially graduates who attended a scientific or technical high school have a greater propensity to enrol in a STEM course than those who come from a humanistic high school. As regards motivations, the value of “cultural motivation" and “neither/nor" coefficients are negative, meaning a lower propensity to enrol in a STEM course compared to graduates driven by both cultural and professional motivation (baseline). In contrast, the coefficient for “more professional" is not significantly different from the baseline value. Family education and social class effects are found to be non-significant, suggesting that they play a limited role in explaining the choice to enrol in STEM in our sample.

Moving to the quantile regression results, Fig. 5 shows the effects of having a STEM degree, being male, and their interaction across the selected quantiles (0.1, 0.25, 0.5, 0.75, 0.9) of the salary distribution. STEM graduates have a positive and significant salary advantage compared to non-STEM graduates in all quantiles except the first. The difference is

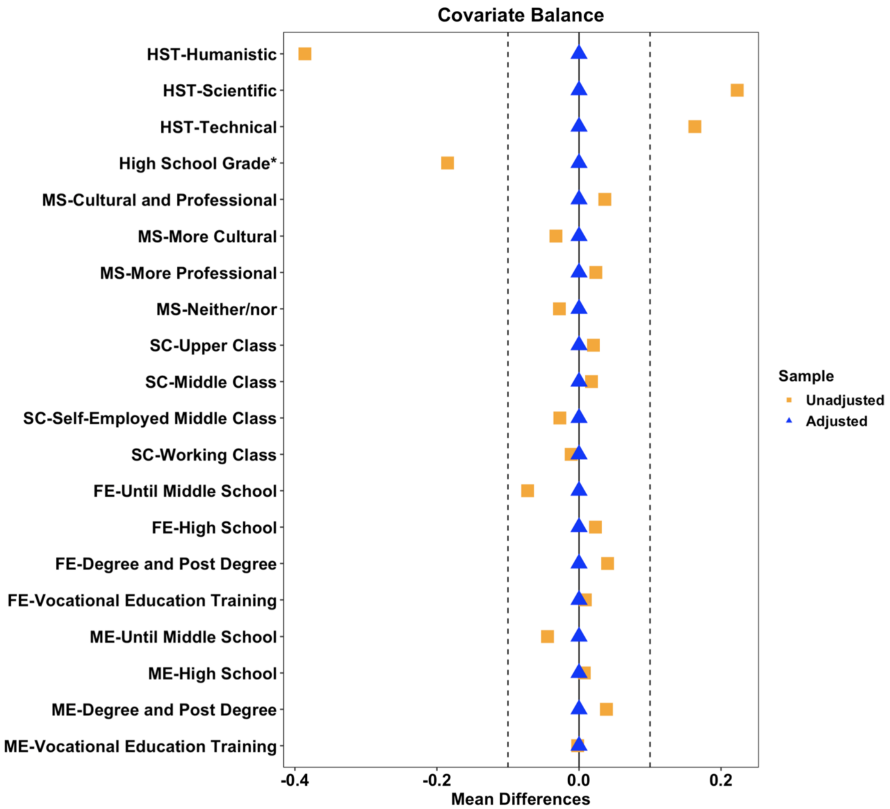

Fig. 4 Love plot: covariate balance before and after PSW. HST: High school type; MS: Motivation to choose a degree; SC: Socio-economic status; FE: Father's education; ME: Mother's education

most evident at the q = 0.25 and around the median, but decreases slightly in the higher quantiles. This pattern suggests that STEM degrees are more relevant for graduates in the lower-middle part of the salary distribution, while the advantage is smaller among high earners. The GPG increases with higher salary. Although not statistically significant in the first decile, meaning that it is minimal among the lowest-paid graduates, the GPG grows with higher salaries and peaks at q = 0.75, where the male salary advantage is around 150 euros. The interaction between gender and STEM degree is generally negative and mostly not significant, indicating that the combined effect of being male and holding a STEM degree is lower than expected if the two advantages were simply additive.

Figure 6 presents the estimated coefficients for the variables use of the degree, type and sector of work, and geographical area. Graduates working in jobs where their degree is required, needed, or at least useful earn more across all quantiles, with the largest advantage at the median and a slight decrease at higher quantiles. Similarly, those in highly skilled jobs have a clear salary advantage that grows with salary levels, while the gap between intermediate and basic jobs is less clear.

Working sector also matters, as salaries are higher in the public sector across all quantiles. The results for the macro areas of work reflect the well-known gap between northern and southern Italy. Compared to graduates working in the south, those employed in the

Table 6 Probit weighted regression estimates for the mediator variable (having a STEM degree), together with their confidence interval (CI) and related *p*-values (significance in bold)

Predictors	$\hat{\beta}_j$	CI	*p*-value
(Intercept)	− 3.45	− 4.03–− 2.87	**<0.001**
Treat: male	1.08	0.94–1.22	**<0.001**
HST-scientific	1.11	0.93–1.28	**<0.001**
HST-technical	0.50	0.27–0.73	**<0.001**
High school grade	0.02	0.02–0.03	**<0.001**
M-more cultural	− 0.37	− 0.55–− 0.19	**<0.001**
M-more professional	0.15	− 0.10–0.40	0.237
M-neither/nor	− 0.49	− 0.72–− 0.27	**<0.001**
FE-degree and post	− 0.13	− 0.33–0.06	0.172
FE-vocational educational training	− 0.06	− 0.27–0.15	0.581
FE-until middle school	0.02	− 0.38–0.41	0.926
ME-degree and post	− 0.05	− 0.23–0.14	0.614
ME-vocational educational training	0.19	− 0.02–0.40	0.071
ME-until middle school	0.13	− 0.35–0.61	0.590
SC-upper class	− 0.04	− 0.25–0.17	0.693
SC-self-employed middle class	− 0.09	− 0.30–0.12	0.423
SC-working class	0.02	− 0.19–0.22	0.860

HST: High school type; M: Motivation to choose a degree; FE: Father's education; ME: Mother's education; SC: Socio-economic status

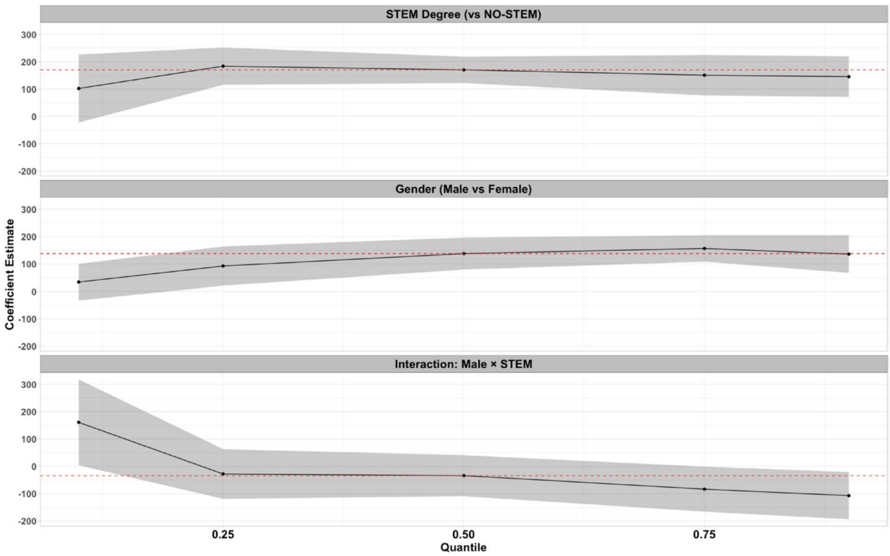

Fig. 5 Quantile regression coefficients with bootstrapped confidence interval at 95% for selected quantiles (0.1, 0.25, 0.5, 0.75, 0.9). The red dashed line represents the ordinary least squares estimate

north, centre or abroad earn higher salaries across all quantiles. This advantage is greater in the lower and middle quantiles and decreases at the top of the salary distribution.

With respect to the causal effects estimates for both groups, the estimated QCMEs (left panel of Fig. 7) are positive and significant for almost all quantiles for both groups, indicating that STEM participation plays an important role as mediator in the relationship between gender and salaries. Among male graduates, the causal mediation effect of a STEM degree

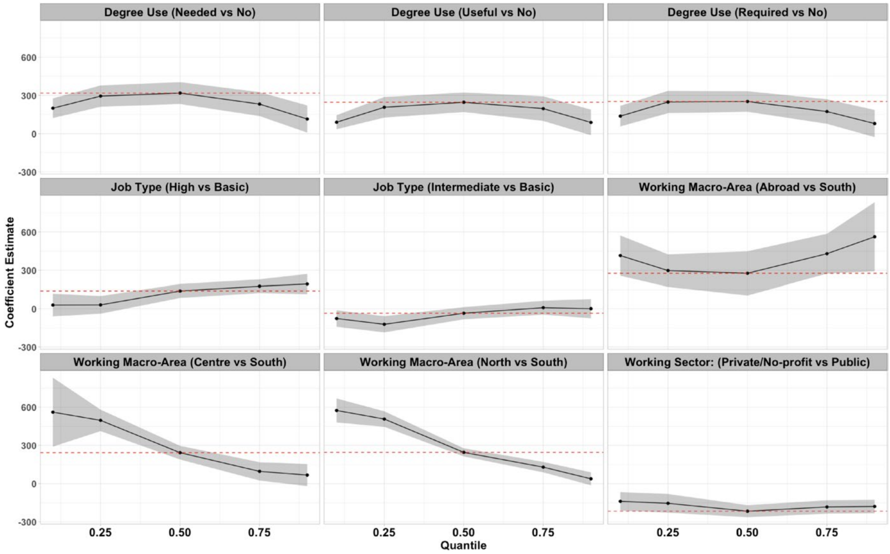

Fig. 6 Quantile regression coefficients with bootstrapped confidence interval at 95% for selected quantiles (0.1, 0.25, 0.5, 0.75, 0.90). The red dashed line represents the ordinary least squares estimate

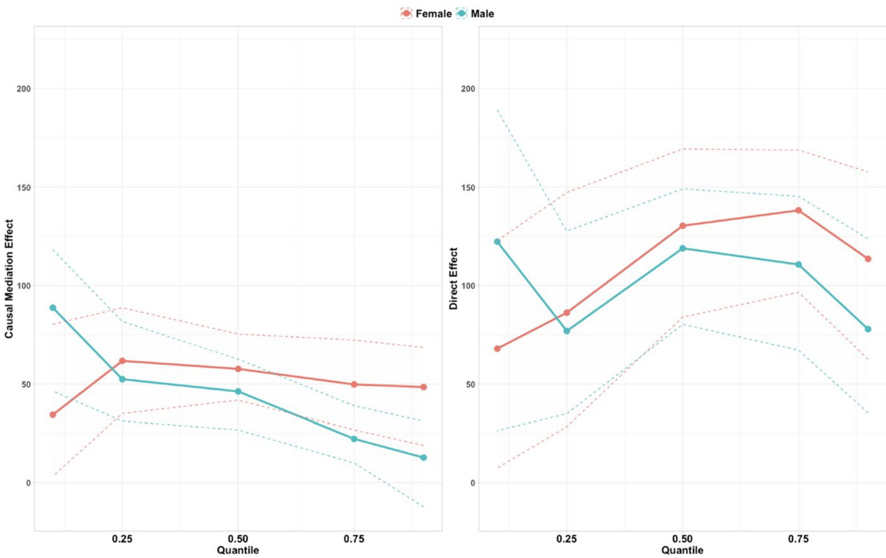

Fig. 7 QCME (left) QDE (right) with dashed bootstrapped confidence interval at 95% for selected quantiles (0.1, 0.25, 0.5, 0.75, 0.9). The red line indicates the female group (control), the blue line indicates the male group (treatment)

is strongest at the bottom of the salary distribution (0.10 quantile) and declines as salary increases, becoming non-significant at the top of the distribution (0.90 quantile). This suggests that male's salary advantage at lower quantiles is substantially driven by their higher participation in STEM fields: if male had the same STEM representation as female, their salaries would drop considerably. For female, the QCME shows a more steady pattern across quantiles, with a slight increase in the lower-middle range (0.10 and 0.25 quantiles) and a constant effect at higher quantiles. This indicates that if the participation rate of women in STEM degrees were equal to that of men, women would have a salary advantage across all quantiles, and that this advantage would be particularly visible in the lower–middle part of the distribution where the QCME is larger, while remaining positive, though slightly smaller, among higher earners.

The QDE, i.e. the part of the GPG that remains after controlling for STEM, is significant in all quantiles and relatively higher than the mediation effect (right panel of Fig. 7). At the bottom of the distribution (q = 0.10), the male Direct Effect is higher than the female one, showing that men have a substantial direct salary advantage. Moving to q = 0.25, the male direct advantage becomes smaller, while the female direct effect grows, so the gap in direct effects is reduced around the lower–middle part of the distribution. From the median onwards, the QDE pattern indicates that the component of the gender gap not explained by STEM is relatively more important for women, suggesting that, among better-paid graduates, non-STEM mechanisms (e.g. sectoral allocation, career progression, contract type) account for a larger share of the observed inequality than differences in field of study. From the median to the upper quantiles (q = 0.50–0.75) the female direct effect exceeds the male direct effect: gender differences that are not explained by STEM become more important for female as salaries increase. In the top decile (q = 0.90) the direct effect for both groups decline but remain positive, indicating that a direct gender gap persists even at the highest salaries. This result may suggest that other factors outside the field of study play a role along the whole distribution, and they become especially important for women among higher earners. Finally, Fig. 8 shows the proportion of the total causal effect mediated by STEM. For males, this means that more than half of the total gender effect among the lowest earners can be attributed to their higher presence in STEM. This mediated share progressively shrinks moving up the salary distribution, until it becomes negligible for the top earners, where other factors dominate (e.g. access to senior leadership roles, or career interruptions). For females, instead, the mediated proportion remains consistently different from zero across quantiles, with values around 40% in the lower–middle part and again close to 40% in the upper tail, indicating that equalising STEM participation would generate sizeable gains both for women with relatively low salaries and for those at the top of the distribution.

Overall, participation in a STEM course explains a substantial part of men's salary advantages, particularly in the lower part of the distribution, and a moderate and significant part of women's potential earnings, for all quantiles. The comparison between direct and mediated effects across the salary distribution reveals that while STEM education plays a significant role in understanding gender salary disparities, it does not fully explain the entire GPG. The larger estimated direct effect may indicate the existence of other mediation factors beyond field of study, such as sectoral occupational segregation, care giving responsibilities, and discriminatory practices. Moreover, the use of overlap weights shifts part of the GPG from the direct effect to the mediation effect through STEM. The increase in mediation effect is greater for both groups in the lower quantiles; in the higher quantiles, this difference is reduced for both groups, with a

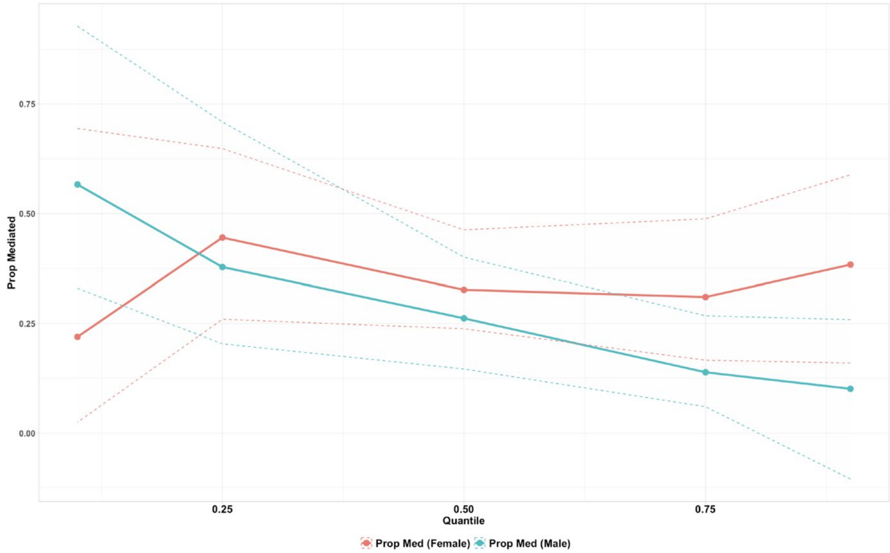

Fig. 8 Proportion of total causal effect mediated by STEM participation with dashed bootstrapped confidence interval at 95% for selected quantiles (0.1, 0.25, 0.5, 0.75, 0.9). The red line indicates the female group (control), the blue line indicates the male group (treatment)

greater reduction for females than for males. Similarly, the direct effect is lower in the weighted model, particularly at q = 0.25.

These results were compared with those obtained using an unweighted approach. With respect to the unweighted case, the differences were fairly smaller. However, the comparison indicates that unweighted analyses tend to underestimate the role of STEM as a mediator and overestimate the residual direct gap, especially in the lower half of the salary distribution.

6 Conclusions

This study contributes to the literature on gender wage inequality by examining the mechanisms linking gender, educational pathways, and early-career salaries through a mediation framework applied to Italian graduate data. Using micro-level information from the University of Palermo, we show that the gender pay gap among recent graduates cannot be attributed solely to gender differences *per se*, but is partly mediated by the choice of field of study, particularly participation in STEM education. By explicitly modelling STEM degree attainment as a mediator, our analysis provides new evidence on how educational trajectories shape early labour-market inequalities, complementing existing research that typically examines either gender wage differentials or STEM participation separately (Blau and Kahn 2017; Blackburn 2017; Petrenko and Cadil 2024). Our results show that the under-representation of women in STEM, already evident from the earliest stages of the educational pipeline (INVALSI 2024; Tocchioni et al. 2022; Priulla et al. 2021) translates into occupational segregation and contributes to persistent salary differentials in the labour market. In line with the findings of Petrenko and Cadil (2024) and Zajkac et al. (2025), we document that women's lower representation in high-paying STEM sectors is a significant driver of salary inequality. Another relevant innovative aspect of our approach is to include not only quantitative information about gender pay gap but also qualitative information such as the social status and the job site (macro-area location). This allows us to take into account specific features of the Italian labour market: male students are more prone to move to the North of Italy, that offers higher job opportunities and salaries (Genova et al. 2019). Results, in fact, suggest that the GPG is not solely a result of background, job type or skill level. It may also reflect institutional, cultural, or policy-related factors such as career progression barriers, part-time employment, or occupational segregation. Actually, personality traits (e.g., risk aversion, ambition), preferences for certain work–life balance arrangements, negotiation behaviour, and informal networks are not observed in our data and may simultaneously affect both the likelihood of enrolling in STEM programmes and salary outcomes (Kahn and Ginther 2017). If these factors should differ systematically by gender and are not adequately proxied by our observed covariates, our PSW-based estimates of QCME and QDE may still be biased. A standard approach to assess robustness to violations of the sequential ignorability assumption is sensitivity analysis (Imai et al. 2010). However, widely used sensitivity procedures for causal mediation are primarily developed for mean-based parametric outcome models, and an analogous sensitivity analysis is not currently available for our quantile-regression-based mediation framework (Imai et al. 2010). Developing or adapting sensitivity-analysis tools for quantile-based mediation models is therefore an important direction for future research. From a policy perspective, our results open the possibility of reducing the gap by encouraging greater female participation in STEM education and by improving retention in STEM careers. International literature (Blackburn 2017; Verdugo-Castro et al. 2022; Cheryan et al. 2025) emphasizes that structural barriers, gender stereotypes, and self-efficacy differences discourage women from pursuing and persisting in STEM. Interventions aimed at promoting positive self-concept, addressing cultural biases, and creating more inclusive academic and workplace environments are therefore crucial. At the same time, our work leaves room for future developments. First, to overcome the data limitation above mentioned, the analysis could be extended and generalized to the entire Italian population of graduates, in order to verify the external validity of the findings (or assess the stability of the QCME and QDE patterns across different institutional, cultural, or policy-related factors such as career progression barriers, part-time employment, or occupational segregation. Actually, personality traits (e.g., risk aversion, ambition), preferences for certain work–life balance arrangements, negotiation behaviour, and informal networks are not observed in our data and may simultaneously affect both the likelihood of enrolling in STEM programmes and salary outcomes (Kahn and Ginther 2017). If these factors should differ systematically by gender and are not adequately proxied by our observed covariates, our PSW-based estimates of QCME and QDE may still be biased. A standard approach to assess robustness to violations of sequential ignorability is sensitivity analysis (Imai et al. 2010). However, widely used sensitivity procedures for causal mediation are primarily developed for mean-based parametric outcome models, and an analogous sensitivity analysis is not currently available for our quantile-regression-based mediation framework (Imai et al. 2010). Developing or adapting sensitivity-analysis tools for quantile-based mediation models is therefore an important direction for future research.

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Author contributions This article is the result of a collective effort. All authors contributed to the overall design of the study, engaged in substantive discussions at each stage of the writing process, and share full responsibility for the integrity of the final manuscript. Authors Giambalvo and Vittorietti drafted Sects. 1 and 2; authors Boscaino, La Mantia and Vittorietti developed Sect. 3; Boscaino developed Sect. 4; all authors contributed to the Results and Conclusions. Author La Mantia is responsible of the data curation. All authors have read and approved the final manuscript.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no conflict of interest.

References

Addabbo, T., Favaro, D., Magrini, S., et al.: The distribution of the gender wage gap in italy: does education matter? Recent working paper series (2007)
Alkadry, M.G., Tower, L.E.: Unequal pay: the role of gender. Public Adm. Rev. **66**(6), 888–898 (2006)
AlmaLaurea.: Focus gender gap 2023. https://www.almalaurea.it/news/focus-gender-gap-2023. (2023). Accessed Oct 2025
AlmaLaurea.: Laurea STEM: verso una riduzione del gender gap. (2025)
Andreotti, A., Mingione, E., Pratschke, J.: Female employment and the economic crisis: social change in northern and southern Italy. Eur. Soc. **15**(4), 617–635 (2013)
Barbieri, P., Cutuli, G., Lugo, M., et al.: The role of gender and education in early labor market careers: long-term trends in italy. Gender, education and employment: an international comparison of school-to-work transitions pp 142–160 (2015)
Bellomo, S., Croce, G., Di Gravio, G., et al.: Dinamica dei redditi recenti squilibri nell'industria italiana. L'industria **46**(1), 129–159 (2025)
Bind, M.A., VanderWeele, T., Schwartz, J., et al.: Quantile causal mediation analysis allowing longitudinal data. Stat. Med. **36**(26), 4182–4195 (2017)
Bishu, S.G., Alkadry, M.G.: A systematic review of the gender pay gap and factors that predict it. Adm. Soc. **49**(1), 65–104 (2017)
Blackburn, H.: The status of women in stem in higher education: a review of the literature 2007–2017. Sci. Technol. Libr. **36**(3), 235–273 (2017)
Blau, F.D., Kahn, L.M.: The gender wage gap: extent, trends, and explanations. J. Econ. Lit. **55**(3), 789–865 (2017)
Carreras, M.: what do we have to lose?: local economic decline, prospect theory, and support for brexit. Elect. Stud. **62**, 102094 (2019)
Castellano, R., Rocca, A.: On the unexplained causes of the gender gap in the labour market. Int. J. Soc. Econ. **47**(7), 933–949 (2020)
Cheryan, S., Lombard, E.J., Hailu, F., et al.: Global patterns of gender disparities in stem and explanations for their persistence. Nature Rev. Psychol. **4**(1), 6–19 (2025)
Chi, W.E., Huang, S., Jeon, M., et al.: A practical guide to causal mediation analysis: illustration with a comprehensive college transition program and nonprogram peer and faculty interactions. In: Frontiers in Education, Frontiers Media SA, pp. 886722 (2022)
Daniele, V.: Produttività, salari e prezzi nelle regioni italiane. Reg. Econ. **6**(Q3), 3–14 (2022)
Dasgupta, N., Stout, J.G.: Girls and women in science, technology, engineering, and mathematics: steming the tide and broadening participation in stem careers. Policy Insights Behav. Brain Sci. **1**(1), 21–29 (2014)
De Gioannis, E.: Gender-essentialist beliefs and the gender gap in stem: evidence on the gender-essentialism theory. Qual. Quant. **59**(Suppl 2), 1229–1251 (2025)
Diekman, A.B., Weisgram, E.S., Belanger, A.L.: New routes to recruiting and retaining women in stem: policy implications of a communal goal congruity perspective. Soc. Issues Policy Rev. **9**(1), 52–88 (2015)
Encinas-Martín, M., Cherian, M.: Gender. Educ. Skills. OECD. (2023). https://doi.org/10.1787/34680dd5-en
European Institute for Gender Equality.: Gender equality index 2024: Sustaining momentum on a fragile path. (2024)
Ferri, V., García-Pereiro, T., Pace, R.: Gender pay-gap: exploring the school-to-work transition of graduates in Italy. Int. J. Manpow. **44**(6), 1143–1167 (2023)
Fortin, N., Frey, V.: Persistent gender pay gaps: drivers and policy levers. In: Handbook on Labour Markets in Transition. Edward Elgar Publishing, pp. 483–499 (2024)
Giambalvo, O., Palumbo, S.: Il lavoro dei giovani AI tempi della pandemia. Le Nuove Frontiere della Scuola **54**, 76–88 (2021)
Goldin, C.: Understanding the Gender Wage Gap: An Economic History of American Women. Oxford University Press, New York (1990)
Hu, A., Mustillo, S.A.: Recent development of propensity score methods in observational studies: multi-categorical treatment, causal mediation, and heterogeneity. Curr. Sociol. **64**(1), 60–82 (2016)
Huang, M.L., Xu, X., Tashnev, D.: A weighted linear quantile regression. J. Stat. Comput. Simul. **85**(13), 2596–2618 (2015)
Imai, K., Keele, L., Tingley, D.: A general approach to causal mediation analysis. Psychol. Methods **15**(4), 309 (2010)
ISTAT.: Open scuola: iscrizioni anno scolastico 2020/2021. https://dati.istruzione.it/opendata/, dati su iscrizioni scuole superiori per genere e indirizzo. (2021)

ISTAT.: La struttura delle retribuzioni in Italia: Anno 2022. Statistica report, ISTAT, https://www.istat.it/it/archivio/204531. (2025a)

ISTAT.: Rapporto annuale 2025. la situazione del paese. Tech. rep., ISTAT, Roma, https://www.istat.it. (2025b). capitolo 4: Sistema economico e generazioni

Kahn, S., Ginther, D.: Women and Stem. Tech. rep, National Bureau of Economic Research (2017)

Kang, J., Hense, J., Scheersoi, A., et al.: Gender study on the relationships between science interest and future career perspectives. Int. J. Sci. Educ. **41**(1), 80–101 (2019)

Koenker, R.: Quantile Regression, vol. 38. Cambridge University Press (2005)

Koenker, R., Portnoy, S., Ng, P.T., et al.: Package 'quantreg'. Reference manual available at R-CRAN: https://cran rproject org/web/packages/quantreg/quantreg pdf. (2018).

Krause, S.F.: Leadership: Underrepresentation of women in higher education. Northcentral University (2017)

Lahuerta, S.B., Miller, K., Carlson, L.: Introduction: pay inequity-old problems, new solutions? In: Bridging the Gender Pay Gap through Transparency. Edward Elgar Publishing, pp. 1–31 (2024)

Li, F., Morgan, K.L., Zaslavsky, A.M.: Balancing covariates via propensity score weighting. J. Am. Stat. Assoc. **113**(521), 390–400 (2018)

McCoy, D.C., Seiden, J., Cuartas, J., et al.: Estimates of a multidimensional index of nurturing care in the next 1000 days of life for children in low-income and middle-income countries: a modelling study. Lancet Child Adolesc. Health **6**(5), 324–334 (2022)

Meoli, A., Piva, E., Righi, H.: Missing women in stem occupations: the impact of university education on the gender gap in graduates' transition to work. Res. Policy **53**(8), 105072 (2024)

Ministero degli Affari Esteri e della Cooperazione Internazionale (2025) Three-year programming and policy planning document (pppd) 2024–2026. https://www.esteri.it/wp-content/uploads/2025/07/Three-year-Programming_Policy-Planning-Document_PPPD_2024-2026.pdf, rome: MAECI

Olivetti, C., Petrongolo, B.: Unequal pay or unequal employment? a cross-country analysis of gender gaps. J. Law Econ. **26**(4), 621–654 (2008)

Petrenko, O., Cadil, J.: Can successful female stem graduates contribute to narrowing the gender pay gap in the EU? Eur. J. Educ. **59**(2), e12641 (2024)

Redmond, P., McGuinness, S.: The gender wage gap in Europe: job preferences, gender convergence and distributional effects. Oxford Bull. Econ. Stat. **81**(3), 564–587 (2019)

Rosenbaum, P.R., Rubin, D.B.: The central role of the propensity score in observational studies for causal effects. Biometrika **70**(1), 41–55 (1983)

Rosenbaum, P.R., Rosenbaum, P., Briskman.: Design of observational studies, vol 10. Springer (2010)

Rubin, D.B.: Estimating causal effects from large data sets using propensity scores. Annals of internal medicine 127(8_Part_2):757–763 (1997)

Sassler, S., Glass, J., Levitte, Y., et al.: The missing women in stem? Assessing gender differentials in the factors associated with transition to first jobs. Soc. Sci. Res. **63**, 192–208 (2017)

Shen, E., Chou, C.P., Pentz, M.A., et al.: Quantile mediation models: a comparison of methods for assessing mediation across the outcome distribution. Multivar. Behav. Res. **49**(5), 471–485 (2014)

Sloane, C.M., Hurst, E.G., Black, D.A.: College majors, occupations, and the gender wage gap. J. Econ. Perspect. **35**(4), 223–248 (2021)

Stewart-Williams, S., Halsey, L.G.: Men, women and stem: why the differences and what should be done? Eur. J. Pers. **35**(1), 3–39 (2021)

Stokke, H.E.: The gender wage gap and the early-career effect: the role of actual experience and education level. Labour **35**(2), 135–162 (2021)

Tingley, D., Yamamoto, T., Hirose, K., et al.: Mediation: R package for causal mediation analysis. J. Stat. Softw. **59**, 1–38 (2014)

Ubenova, R.: Gender gaps in the labor market: an ilo analysis. Tech. rep., International Labour Organisation, Switzerland, (2023) https://coilink.org/20.500.12592/vhg08q, cOI: 20.500.12592/vhg08q

Verdugo-Castro, S., García-Holgado, A., Sánchez-Gómez, M.C.: The gender gap in higher stem studies: a systematic literature review. Heliyon **8**(8), (2022)

Vittorietti, M., Priulla, A., Boscaino, G., et al.: A new bipartite matching approach for record linkage: the case of two big italian databases. In: Book of the short papers. Pearson, pp. 754–760 (2022)

Weichselbaumer, D., Winter-Ebmer, R.: A meta-analysis of the international gender wage gap. J. Econ. Surv. **19**(3), 479–511 (2005)

Xie, Y.: Social influences on science and engineering career decisions. In: Workshop report from the Biological, Social, and Organizational Components of Success for Women in Academic Science and Engineering. National Academies (2006)

Zajkac, T., Magda, I., Bożykowski, M., et al.: Gender pay gaps across stem fields of study. Stud. High. Educ. **50**(1), 126–139 (2025)

Zhou, Y., Matsouaka, R.A., Thomas, L.: Propensity score weighting under limited overlap and model misspecification. Stat. Methods Med. Res. **29**(12), 3721–3756 (2020)

Zizza, R.: The gender wage gap in Italy. Bank of Italy Occasional Paper (172) (2013)
INVALSI (2024) Rapporto invalsi 2024: I risultati delle rilevazioni nazionali. Tech. rep., INVALSI
Tocchioni, V., Galluccio, C., Morabito, M.F., et al (2022) Students enrolled in stem discipline in italy: patterns of retention, dropout and switch. In: Book of the short paper SIS 2022. Pearson
Priulla, A., D'Angelo, N., Attanasio, M. (2021) An analysis of Italian university students' performance through segmented regression models: gender differences in stem courses. Genus 77(1):11
Genova, V., Tumminello, M., Enea, M., Aiello, F., & Attanasio, M. (2019). Student mobility in higher education: Sicilian outflow network and chain migrations. ELECTRONIC JOURNAL OF APPLIED STATISTICAL ANALYSIS, 12(4), 774-800.

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