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Statistical Discrimination Revisited: Explaining the Early Gender Wage Gap with Graduate Data*

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Abstract

This paper revisits the statistical discrimination model of Phelps (1972) to explain why a gender wage gap emerges immediately at labour-market entry, despite women's superior academic performance. We focus on graduates and extend the framework by adding a productivity-relevant attribute -willingness to work abroad or IT skills— that is correlated with gender and differs across fields of study. Employers observe noisy individual signals and coarse group-level statistics by gender and field, and optimally combine them when setting wages. Within this setting, gender differences in the distribution of these attributes can generate an entry wage premium for men even when women have higher average human capital.

We test this mechanism using AlmaLaurea microdata on master's graduates from the University of Bologna (2015–2022). We calibrate the model for the full sample and separately for Economics & Management and Engineering. Human capital alone cannot reproduce the observed wage differences, while augmenting the model with willingness to work abroad or IT skills brings predicted and actual gaps into close alignment. Complementary wage regressions show that mobility intentions explain a substantial share of the raw gender wage gap across fields, whereas IT skills matter primarily in Engineering and only marginally in the aggregate. The combined evidence from the model calibration and the empirical analysis supports an extended statistical discrimination channel operating through gendered distributions of mobility and IT-related attributes.

Keywords: Gender wage gap; statistical discrimination; human capital; mobility intentions; IT skills; field heterogeneity; model calibration.

JEL Classification: J16, J31, J71, J24.

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Non-technical summary

Women consistently perform better than men in school and at university. They achieve higher grades across all fields of study, including Economics and Management and Engineering. Yet, just one year after graduation, they already earn lower wages. This cannot be explained by human capital alone—if pay depended only on academic performance, women should have equal or higher earnings.

To address this puzzle, the study extends the classic model of statistical discrimination (Phelps, 1972), where employers form expectations of productivity based on limited signals. Instead of considering only human capital (grades and field of study), the model also incorporates one of two additional productivity-related traits: Mobility intentions – willingness to move or work abroad, seen as a proxy for ambition, flexibility, and career orientation. IT skills – self-assessed proficiency in digital tools, reflecting technological adaptability and readiness for modern workplaces.

Using microdata from the AlmaLaurea survey of University of Bologna graduates (2015–2022), the study shows that: (i) Women outperform men academically, but men report stronger IT skills and greater willingness to work abroad. (ii) When only human capital is considered, the Phelps' model wrongly predicts a wage advantage for women. (iii) Once mobility intentions or IT skills are added, the model reproduces the actual gender wage gaps observed in Economics/Management, Engineering and in the full sample of graduates. (iv) Mobility intentions matter in all fields, while IT skills are particularly relevant in Engineering, where technological competence is more strongly rewarded.

Regression analysis confirms that willingness to work abroad is associated with significantly higher wages in both fields and overall, while IT skills yield higher pay only in Engineering and in the full sample of graduates. In all cases, part of the gender wage gap can be traced to these traits, which employers may use when evaluating candidates. The findings suggest that employers rely on additional signals of productivity beyond human capital—such as mobility intentions and IT skills—which are unevenly distributed across genders. As policy implications, the paper suggests that efforts to reduce early career gender gaps should promote women's international mobility and strengthening their digital skills. Employers, in turn, should be cautious in relying on group-level stereotypes when assessing candidates, as these practices may reinforce current disparities.

1 Introduction

In statistical discrimination models, employers do not perfectly observe key characteristics of applicants, such as productivity. They therefore combine information on the CV with *group information*, for example average outcomes for men and women, to form expectations at hiring. In Phelps's classic formulation (Phelps, 1972), unequal treatment can arise without prejudice: if two groups differ on average in a productivity-related trait such as human capital, it is rational to offer different wages to otherwise identical candidates from different groups. In the textbook example, when employers correctly believe that a minority has lower average human capital than the dominant group, they tend to offer lower wages to its members, holding the observed CV constant. The logic is informational: group statistics serve as proxies for what is not fully observable at the individual level. Our point is that the salience of group statistics has increased substantially in today's data-rich labor markets, where employers can systematically incorporate gender-disaggregated and field-specific information from administrative databases, placement platforms, and cohort reports into their hiring decisions.[1]

Women can hardly be described as a minority among graduates: they attain tertiary education more often than men (though they remain underrepresented in STEM); see, among others, Bertrand (2020). Moreover, a large body of evidence shows that women perform as well as or better than men academically across fields.[2] If pay at entry mainly reflected human capital, and if CV signals were equally informative across genders, women with a given signal should earn at least as much as comparable men.

Yet women face worse labor-market outcomes soon after graduation—lower wages, lower employment rates, and higher part-time incidence (Bertrand, 2020; Piazzalunga, 2018; Bovini et al., 2024). To reconcile these facts with rational inference, we revisit Phelps by allowing employers to weight, in addition to academic performance, other productivity-relevant attributes that are salient at entry and correlated with gender. We focus on two: *mobility intentions* (willingness to travel or relocate for work) and *IT skills* (technological proficiency). Our idea is that when employers observe that these attributes are systematically distributed differently across male and female job seekers, they complement the public information already derived from gender-specific distributions of human capital. In this setting, statistical inference can generate early gender gaps despite women's superior academic records.

We formalize these mechanisms in a simple extension of the Phelps framework and

[1] In Italy, a key source is *AlmaLaurea*, an inter-university consortium that surveys graduates and disseminates statistics disaggregated by gender and field of study, providing microdata on education-to-work transitions. In this paper, we use AlmaLaurea microdata for University of Bologna master's graduates (2015–2022) to calibrate and empirically assess the model.

[2] See Conger and Long (2010) for the USA, Verbree et al. (2023) for the Netherlands, Carroll (2023) for UK, and Piazzalunga (2018); Bovini et al. (2024) for Italy.

calibrate it using AlmaLaurea data on University of Bologna graduates (2015–2022). We then test whether the extended model can account for the observed early gender wage gap overall and within Economics & Management and Engineering, highlighting field-specific salience of mobility intentions and IT skills.

We situate our approach within a growing literature documenting that preferences over job attributes and technology-related competencies shape early labor-market outcomes. A broad set of studies links gender differences in commuting and geographic mobility to sorting, job matching, and wage trajectories, indicating that women are less willing to accept long commutes or relocations even conditional on observables (e.g., Le Barbanchon et al., 2021; Liu and Su, 2024; Havet et al., 2021; Cortés et al., 2023; Abraham et al., 2019). In parallel, work on digital skills shows that IT-related competencies have become a core component of productivity and remuneration, with gender gaps in technological proficiency contributing to wage differences where such skills are strongly rewarded (e.g., Hargittai, 2002; Black and Spitz-Öener, 2010; Cortés and Goldin, 2020; Bustelo, 2019; Zhang, 2024). We build on these insights by formalizing how mobility intentions and IT skills enter employers' expectations at entry as productivity-relevant attributes correlated with gender.

Our calibration uses AlmaLaurea survey microdata on University of Bologna master's graduates (2015–2022), interviewed one year after graduation and spanning all fields of study. Two motivating facts emerge. First, women outperform men in GPA across fields. Second, despite this advantage, women earn less, are less likely to be employed, and more often work part-time one year after graduation (Bertrand, 2020; Piazzalunga, 2018; Bovini et al., 2024). If entry pay primarily reflected human capital and CV signals were equally informative across genders, these outcomes would be hard to reconcile. Our extended framework addresses this tension.

We study the full cohort of graduates across all fields and then provide two focused deep dives in Economics & Management and in Engineering to illustrate theoretically meaningful and empirically salient field heterogeneity. These two areas differ in gender composition and in how the attributes we study are rewarded: geographic mobility tends to matter more where international assignments and relocation are common, while IT skills are more tightly linked to productivity and pay in technologically intensive settings. Analyzing them separately enables cleaner within-field comparisons of opportunities and constraints and clarifies where each attribute carries more weight.

We deliver three main findings. (i) With human capital alone, Phelps' model does not generate a male wage advantage given women's GPA lead. (ii) Incorporating *mobility intentions* reproduces the early female wage penalty in the aggregate sample (all fields of study) and within Economics & Management and Engineering. (iii) *IT skills* further improve fit where technological competencies are more strongly rewarded, particularly in Engineering. Together, these results show how rational group-based inference on productivity-relevant attributes can produce a male wage advantage at entry, even when women hold stronger academic records.

The remainder of the paper is structured as follows. The following subsection describes the related literature. Section 2 presents descriptive evidence that motivates our analysis, highlighting the coexistence of women's higher academic performance and lower early labor market wages, as well as systematic gender differences in productivity-relevant attributes—both mobility intentions and IT skills. Section 3 introduces the statistical discrimination model, calibrated using measures of human capital alongside productivity-relevant attributes. Section 4 tests whether the extended Phelps' model can account for the early gender wage gap documented and examines, in turn, the role of mobility intentions and IT skills in explaining its magnitude across fields. Section 5 concludes.

1.1 Related literature

The theoretical model builds on the literature on statistical discrimination, pioneered by Arrow (1971) and Phelps (1972).[3] In the tradition of Arrow (1971), group differences can emerge endogenously, even when groups are identical in ability, as a self-fulfilling prophecy. For example, Coate and Loury (1993) show that if employers believe one group to be less productive, members of that group, anticipating lower returns, invest less in human capital, thereby confirming the initial belief.

In the Phelps (1972) tradition, employers have imperfect information on productivity, and the distribution of productivity signals differs exogenously across groups (e.g., by race, gender, or social category). Aigner and Cain (1977) introduce employer risk aversion and show that when signals for one group are noisier, a risk-averse employer discounts them more, leading to lower average wages despite equal mean productivity. Lundberg and Startz (1983) extend this framework by allowing workers to choose costly skill investments before entering the labor market; if one group's signals are noisier, the returns to investment are lower, reducing incentives to acquire skills and leading to lower human capital in equilibrium. Cornell and Welch (1996) analyze a tournament setting in which firms hire the single best candidate and show that discrimination can arise if one group's signals are more precise or more numerous. Recent contributions have extended the theory of statistical discrimination. Craig (2018) develops a two-sided model of statistical discrimination, and Chambers and Echenique (2021) formally characterize the conditions under which Phelpsian discrimination arises. Yet these papers are not explicitly focused on gender.

[3] Fang and Moro (2011) provide a comprehensive survey.

The paper is also related to the theoretical and empirical literature on gender-wage gap. Goldin (1986) provides a broad historical account of women's economic outcomes in the United States, in which statistical discrimination is cited among the mechanisms shaping persistent wage gaps. More recently, Altonji and Blank (1999) review both race and gender disparities in the labor market and explicitly discuss statistical discrimination as one of the canonical models, while Grybaite (2006) surveys theoretical approaches to the gender pay gap. Bertrand and Hallock (2001) examine the scarcity of women in top corporate roles and find that even amid rising female participation, a substantial gender gap persists at the executive level. For example, they observe that women executives are often concentrated in smaller firms and are less likely to be CEOs, which explains a large portion of the pay gap. Likewise, using Swedish data, Albrecht et al. (2003) find that the gender wage gap not only persists but actually widens at the top of the wage distribution. They interpret this pronounced upper-tail gap through the lens of statistical discrimination. This suggests that, as women approach the highest-paying jobs, employers increasingly rely on gender-based assumptions about productivity or career dedication. This limits women's pay and advancement in top positions. Finally, Blau and Kahn (2017) provide new empirical evidence from 1980 to 2010 documenting a substantial decline in the gender wage gap over this period. They also survey the literature on the gender wage gap, reaffirming that traditional explanations, such as those in Phelps (1972), remain relevant for understanding persistent gender differences in earnings. They emphasize that, although factors such as human capital, work experience, and occupational segregation explain much of the reduction in the gender wage gap over time, a residual gap persists. This residual portion is consistent with statistical discrimination, employer gender-based expectations, and stereotypes that continue to influence pay and opportunities, even when men and women have similar qualifications.

Our model follows Phelps (1972)'s approach, extending it to incorporate observable statistics on job candidates' human capital together with other productivity-relevant attributes, like mobility intentions and IT skills. Employers, in this framework, form expectations not only from academic performance but also from these attributes that are unevenly distributed across genders and fields of study. To the best of our knowledge, no prior work has directly applied the Phelps (1972) model to the very start of workers' careers, nor integrated such preference- and skill-based dimensions into the framework. Our contribution is therefore novel in showing that adding these productivity-relevant attributes allows the Phelps' model to reproduce the early gender wage gap among recent graduates, while also highlighting that those attributes matter differently across fields.

2 Motivating evidence

Before presenting the theoretical framework, we document two motivating facts for University of Bologna graduates. First, women consistently outperform men academically—achieving higher average GPAs—yet they earn lower wages one year after graduation. Second, there are systematic gender differences in two productivity-relevant attributes: mobility intentions and IT skills. These attributes show only a very weak correlation with graduates' GPA.

A detailed description of the dataset is provided in Section 4.1, below we describe the relevant variables for our motivating facts. We examine the full sample across all fields of study to establish a comprehensive benchmark, and graduates in Economics & Management and Engineering separately. These two fields differ markedly in gender composition,[4] stereotypes, and career trajectories, yet both are characterized by strong international prospects and high employability. This makes them particularly suitable for joint analysis and comparison in our setting.

Table 1 shows average GPA and average wage one year after graduation, by gender, for the full sample and, separately, for Economics & Management and for Engineering.[5] Note that grades in Italian tertiary education are reported on a 30-point scale (18 = pass, 30 = maximum), and Table 1 presents the corresponding average grades. Table 1 also shows that gender differences in both GPA and average monthly wage reach high statistical significance. To complement these averages, Figures A.2–A.1 in Appendix A plot trends in average wages one year after graduation by gender and graduation cohort for the overall sample and the fields of interest, respectively. A persistent and sizable gender wage gap is visible one year after graduation.

In addition to human capital, which is proxied by students' GPAs, we focus on two productivity-relevant attributes that employers can typically infer from a job candidate's CV: willingness to relocate for work and IT skills. Both are derived from the information available in the AlmaLaurea dataset. First, we measure willingness to relocate for work using the question: "*Are you willing to work abroad?*" Responses are coded on a 1–5 scale: 1 = "Absolutely not", 2 = "More no than yes", 3 = "Neither yes nor no", 4 = "More yes than no", 5 = "Definitely yes". Mobility intentions capture geographic flexibility, which may proxy for ambition, adaptability, or openness to career opportunities that require relocation.

Second, we construct a measure of IT skills from self-assessed proficiency in eleven specific areas: operating systems ($SOLIV$), programming languages ($LPROGLIV$), word

[4]According to AlmaLaurea, women represent about 46% of graduates in Economics & Management and 23% in Engineering.

[5]See Piazzalunga (2018) and Bovini et al. (2024) for evidence that these patterns extend beyond the University of Bologna: across all Italian public universities, women outperform men in GPA yet lag behind in wages.

Table 1: Motivating Facts: GPA and Wages by Gender across All Fields, Economics & Management, and Engineering

	All Fields		Economics&Management		Engineering	
	Men	Women	Men	Women	Men	Women
Average GPA (min grade 18, max 30)	26.69	27.06	26.63	26.87	26.82	27.36
Average monthly wage (€)	1461.56	1334.57	1474.30	1373.41	1515.14	1433.53
	t-tests Men vs Women					
t-statistic (Monthly wage)	21.79		7.35		6.44	
p-value	0.000***		0.000***		0.000***	
t-statistic (GPA)	-13.71		-3.42		-7.46	
p-value	0.000***		0.000***		0.000***	

Notes: This table reports average GPA (on a 30-point scale) and average monthly wages (in euros) by gender and field of study for graduates one year after completion. The t-tests assess whether mean differences between men and women are statistically significant. The table highlights two key motivating facts: women systematically outperform men in academic achievement, yet earn significantly lower wages across all fields. Source: AlmaLaurea survey data, University of Bologna graduates, 2015–2022.

processors (*WPLIV*), spreadsheets (*WSLIV*), databases (*DBLIV*), computer-aided design (*CADLIV*), internet navigation and online communication (*GNETNAV*), website creation and management (*GNETDOSITE*), data networks and protocols (*GNETNET*), multimedia production and editing (*MMEDIALIV*), and presentation software (*GPRES*). Responses are again coded on a 1-5 scale: 1 = "none," 2 = "limited," 3 = "fair," 4 = "good," 5 ="excellent."

For each area $k \in \{1, \ldots, 11\}$, we define:

$$D_{ik} = \begin{cases} 1 & \text{if respondent } i \text{ reports "good" or "excellent" proficiency in area } k, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

We then compute the unweighted sum

$$IT\_skills_i^{continuous} = \sum_{k=1}^{11} D_{ik}, \tag{2}$$

which ranges from 0 to 11. Finally, to facilitate comparison with willingness to work abroad and other covariates, we transform this measure into quintiles:

$$IT\_skills_i = \text{quintiles}\left(IT\_skills_i^{continuous}\right). \tag{3}$$

This quintile analysis ensures that the two productivity-relevant attributes are treated consistently, allowing us to explore their role in shaping gender wage differentials both overall and across fields of study. To ensure a common discrete support, below GPA is also grouped into quintiles as follows: Q1 = 18–21, Q2 = 22–25, Q3 = 26, Q4 = 27–28, Q5 = 29–30.

We now focus on the relationships among GPA, mobility intentions, and IT skills. The contrast between strong academic achievement and the two productivity-relevant attributes is illustrated in Table 2, which reports correlations between GPA and willingness to work abroad, and between GPA and IT skills. For IT skills, the last two columns show very weak but statistically significant correlations in the full sample. Within the specific fields of study, correlations remain weak, and statistical significance decreases. For willingness to work abroad, associations are statistically significant only among women in the full sample and among graduates in Economics & Management. However, even when they reach statistical significance, the magnitudes of the correlation coefficients remain small—the largest, in absolute value, is 0.0754 for GPA and willingness to work abroad among women in Economics & Management. Overall, the results in Table 2 indicate that academic performance is largely orthogonal to both mobility intentions and IT skills, in the full sample and by field.

Table 2: Correlation between GPA and Availability to Work Abroad, and GPA and IT Skills by Gender and Field of Study

	GPA & Abroad		GPA & IT Skills	
Field of study and gender	Corr coeff.	p-value	Corr. coeff.	p-value
All fields (Men)	-0.0048	0.6139	0.0381	0.0000***
All fields (Women)	0.0500	0.0000***	0.0236	0.0093***
Economics & Man. (Men)	0.0489	0.0292**	0.0651	0.0026***
Economics & Man. (Women)	0.0754	0.0014**	0.0384	0.0976*
Engineering (Men)	-0.0224	0.1828	0.0416	0.0119**
Engineering (Women)	0.0191	0.5285	0.0098	0.7440

Notes: This table reports pairwise correlations between GPA and two productivity-related attributes—willingness to work abroad and IT skills—by gender and field of study. Correlations are generally small, indicating that academic performance is largely orthogonal to these traits. This supports treating mobility intentions and IT skills as distinct dimensions of productivity in the analysis. Source: AlmaLaurea survey data, University of Bologna graduates, 2015–2022.

In the Appendix, the three panels of Figure A.4 compares GPA, willingness to work abroad, and IT skills across their respective *quintile distributions* by gender, in the full sample and in the two specific fields of study. These panels show how GPA, willingness to work abroad, and IT skills differ systematically by gender. Women consistently report higher GPAs but lower willingness to work abroad and weaker IT skills. In the top GPA quintiles, the contrast is particularly marked: women dominate in academic performance, while men lead in mobility intentions and IT proficiency. Comparison of the three panels of Figure Figure A.4 indicates that these patterns are robust across disciplines. In addition, the correlation between mobility intentions and IT skills is very low—around 0.09 to 0.13 across groups (see Appendix Table A.1)—indicating only a weak association between these two attributes.

Table 3 documents that, in both the full sample and within-field comparisons, men report higher willingness to work abroad and higher self-reported IT skills than women. These differences are statistically significant at the 5% level (two-sided tests) across fields, except for IT skills among Economics & Management graduates, where the gender gap is not statistically distinguishable from zero. This pattern points to two plausible channels through which gender wage gaps may emerge at labor-market entry. As mentioned above, willingness to work abroad and IT skills have been shown in prior research to affect job sorting and wage disparities through differences in geographic mobility and technological proficiency (e.g., Le Barbanchon et al., 2021; Black and Spitz-Oener, 2007; Cortés et al., 2020; Bustelo, 2019).

Table 3: Motivating Facts: Mobility Intentions and IT Skills by Gender and Field of Study

	All Fields		Economics&Management		Engineering	
	Men	Women	Men	Women	Men	Women
Availability to work abroad	3.88	3.61	3.93	3.55	3.89	3.72
IT skills (quintiles)	3.08	2.68	2.87	2.91	3.61	3.37
	t-tests Men vs Women					
Available to work abroad	19.02		10.94		4.99	
p-value	0.000***		0.000***		0.000***	
IT skills	21.01		-0.97		4.94	
p-value	0.000***		0.331		0.000***	

Notes: The table reports average willingness to work abroad and average IT skills (quintiles) by gender and field of study, together with t-tests for gender differences. Men consistently report higher mobility intentions and stronger IT skills, except for IT skills in Economics & Management, where no significant gender gap is observed. Source: AlmaLaurea survey data, University of Bologna graduates, 2015–2022.

These insights motivate our extension of Phelps (1972), in which productivity depends not only on human capital but also on job mobility-related preferences and IT skills. By including these additional productivity-relevant attributes in the analysis, we capture how gender differences in both geographic flexibility and IT proficiency may influence employers' beliefs and salary choices.

3 Statistical Discrimination Revisited

We propose a variation of Phelps (1972) statistical discrimination model that highlights gender differences. Unlike the seminal model, which focuses exclusively on human capital, our model incorporates an additional productivity-relevant attribute—such as mobility intentions or IT skills—that employers may interpret as a proxy for candidates' motivation, perseverance, and flexibility (see the literature cited in the Introduction and in the previous section presenting motivating evidence).

Consider an economy in which a large cohort of *graduates* enters the labor market. Since our extension of the statistical-discrimination framework is motivated by the growing availability of publicly accessible descriptive statistics on graduates, we restrict attention to job-market applicants at the point of graduation from tertiary education. Employers set wages equal to their expectation of each applicant's productivity.[6]

We assume that productivity is given by

$$\pi = \theta + h + a, \tag{4}$$

where θ represents innate ability, h is human capital, and a is an additional productivity-relevant attribute (in our motivating example, either willingness to work abroad or IT skills). In words, productivity has an innate component and a component shaped by human capital and another productivity-related factor. The term a captures our extension of the Phelps (1972) statistical discrimination framework.

Productivity cannot be directly observed. Employers receive a CV from each graduate and use it as a *private signal* of productivity since the CV contains specific information about the graduate's acquired human capital, h, the other component of productivity, a, and further idiosyncratic information on the graduate. Additionally, employers may use gender and the academic background of the candidates (their field of study) as a *public signal* of productivity, as long as the distribution of h and a systematically vary across gender and field of study in the candidates' population.

Regarding gender differences in acquired human capital, we document female students' better academic performance in Table 1. Interpreting a as willingness to work abroad or IT skills, gender gaps are documented by the existing empirical literature. Our descriptive statistics in Table 3 show that a gender gap in favor of men is systematically observed in our dataset; the only exception concerns IT skills for graduates in Economics & Management, where we do not observe gender differences. However, the distribution of IT skills for men and women in Economics & Management may still differ in terms of precision, as we show below.

[6]To keep things simple, we abstract away from unemployment. This could easily be implemented in our framework without providing much additional insight.

Not only gender but also the field of study matters as a publicly observable stratifier. In our setting and data, publicly available statistics are disaggregated by gender and field, and fields channel translates into distinct labor-market segments with different payoffs to h and a. It is therefore rational for employers to condition wage offers on gender and field of study. Note that information on distributions by gender and fields of study is publicly available and likely observable by employers via gender-disaggregated and field-specific information from administrative databases, placement platforms, and cohort reports. However, when one considers the full sample of graduates, obviously, the field of study does not matter, and gender remains the only public signal. Below, we explain all this in detail.

Graduates

There are two populations of graduates, one of males and one of females. Gender is denoted as $g \in \{m, f\}$. In addition, graduates are associated with a field of study, denoted by t ("topic").

Each graduate of both populations is endowed with innate ability θ, normally distributed according to $\theta \sim \mathcal{N}\left(0, \sigma_\theta^2\right)$.[7] In what follows, it is convenient to use the precision of the distribution $\rho_\theta = \frac{1}{\sigma_\theta^2}$.

During their university studies, graduates acquire human capital h, a one-dimensional measure of academic achievement and acquired skills. Human capital is normally distributed according to gender g and field of study t:

$$h_{gt} \sim \mathcal{N}\left(\overline{h}_{gt}, \frac{1}{\rho_{h_{gt}}}\right); \tag{5}$$

where $\overline{h}_{gt}$ and $\frac{1}{\rho_{h_{gt}}}$ indicate the average human capital in group g and field of study t and its precision, respectively.

The third component of productivity, a, is unrelated to the level of human capital. In our motivating example, this is documented by Table 2 reporting correlations between GPA and mobility intentions and GPA and IT skills. The normal distribution of a depends on gender g and field of study t:

$$a_{gt} \sim \mathcal{N}\left(\overline{a}_{gt}, \frac{1}{\rho_{a_{gt}}}\right), \tag{6}$$

where $\overline{a}_{gt}$ and $\frac{1}{\rho_{a_{gt}}}$ indicate the average productivity-relevant attribute in group g and field of study t and its precision, respectively.

In what follows, we make the following assumption.

[7] As in MacLeod and Urquiola (2015), innate ability may be negative; individuals with low θ can partially offset it through human capital h and, in our extension, the additional attribute a.

Assumption 1. *Suppose* $\overline{h}_{ft} > \overline{h}_{mt}$ *and* $\overline{a}_{ft} \leq \overline{a}_{mt}$ $\forall t$.

Assumption 1 is consistent with the descriptive evidence from our sample presented in Section 2. The first inequality states that, on average, female graduates perform better at university across all fields of study: in particular, female GPA is higher than male GPA, $\overline{h}_{ft} > \overline{h}_{mt}$, as shown in Table 1. This finding is in line with the broader evidence on Italian graduates reported by Piazzalunga (2018) and Bovini et al. (2024) based on alternative datasets.
The second inequality of Assumption 1, $\overline{a}_{ft} \leq \overline{a}_{mt}$, is motivated by Table 3. Specifically, in both fields of study and in the full sample of graduates, male graduates, on average, report greater willingness to work abroad and higher IT skills, with the only exception being IT skills in Economics & Management. Regarding willingness to work abroad, our findings are consistent with Le Barbanchon et al. (2021) and Liu and Su (2024), whereas the evidence on IT skills aligns with men's higher IT proficiency documented by Hargittai (2002), Cortés et al. (2020), and Bustelo (2019).

By contrast, we impose no assumptions on the relative precisions of these distributions. Hence, $\rho_{h_{ft}} \gtrless \rho_{h_{mt}}$ and $\rho_{a_{ft}} \gtrless \rho_{a_{mt}}$.

Signals

As mentioned before, innate ability, human capital, and the additional component of productivity are not directly observable by recruiters. Instead, employers rely on three signals to infer a candidate's productivity. The first is a private signal specific to each candidate (such as information in the CV). The other two are public signals. Their informative content stems from the availability of group statistics from administrative databases and graduates' reports disaggregated by gender and field of study.

- the graduate's *curriculum vitae* (CV), denoted by c;
- the graduate's gender, g;
- the graduate's field of study, t.

The CV is a private signal of productivity because it contains specific information about the candidate's human capital, such as high school final grade and university GPA. It also contains idiosyncratic information on non-academic traits, such as experiences abroad, explicit claims of mobility intentions, and IT skills. Hence, an individual i's curriculum is given by:

$$c_i = \theta_i + h_i + a_i + \varepsilon_i. \tag{7}$$

where ε_i is a normally distributed error term,

$$\varepsilon_i \sim \mathcal{N}\left(0, \frac{1}{\rho_c}\right),$$

capturing the noise in the CV as a signal of the candidate's overall productivity.

The additive specification in equation (7) entails independence between human capital and the additional component of productivity. Evidence from Table 2 indicates that this condition appears to be satisfied in our data, both for willingness to work abroad and IT skills.

As long as human capital and the additional component of productivity are distributed differently across genders and fields of study, employers rationally treat gender and field of study as public signals of productivity. Hence, employers acquire information from the distribution of human capital h and the productivity-relevant attribute a within a given group (male or female graduates in a specific field of study).

Labor market

The labor market is perfectly competitive and each worker is paid his/her expected productivity, denoted as

$$w_{igt} = E\left(\pi_i | c_i, g, t\right). \tag{8}$$

Recall that expected productivity depends on the information contained in the CV (the private signal), as well as on the distribution of human capital and the additional productivity component across gender and field of study (which together constitute the public signals). From Bayes rule (DeGroot, 2005), equation (8) can be expanded to determine the relevance of each signal:

$$w_{igt}(c_i) = \frac{\rho_{h_{gt}}}{\rho_{h_{gt}} + \rho_{a_{gt}} + \rho_c}\overline{h}_{gt} + \frac{\rho_{a_{gt}}}{\rho_{h_{gt}} + \rho_{a_{gt}} + \rho_c}\overline{a}_{gt} + \frac{\rho_c}{\rho_{h_{gt}} + \rho_{a_{gt}} + \rho_c}c_i. \tag{9}$$

In general, the entry salary offered to candidate i of gender g and field of study t depends on both the precision and the average of the distributions of human capital and of the additional productivity component, as well as on idiosyncratic features contained in the CV, captured by a random error term with precision ρ_c. In particular, the first two terms on the right-hand side of equation (9) capture the share of expected productivity inferred from the public signals. The third term, instead, represents the share of expected salary explained by the private signal.

Equation (9) highlights the role of signals' precision in determining expected salary. When the distributions of human capital and of the additional productivity component are relatively less dispersed than the distribution of the private signal ($\rho_{h_{gt}} \geq \rho_c$ and/or $\rho_{a_{gt}} \geq \rho_c$), the marginal contribution of the CV to explaining an individual's productivity becomes relatively small. The opposite applies if the CV is a relatively more accurate measure of productivity. In this latter case, employers evaluating a graduate with an above-average CV, given her or his group gt, will attribute the positive result to high productivity.

Note that the model still applies even when employers do not observe group statistics by field of study. In that case, the second public signal, t, is lost, and the distributions of human capital in (5) and of the productivity-relevant attribute (6) are no longer indexed by t. In terms of our empirical calibration, this is equivalent to applying the model to the entire sample of graduates and considering only gender as the public signal.

To understand the relevance of gender as a public signal, it is useful to study the relationship between individual performance indicated in the CV, c_i, and a candidate's wage, $w_{igt}(c_i)$, and see how it differs by gender. This allows us to test the model's predictions regarding the gender wage gap. Equation (9) shows that this relationship is linear, with intercept

$$I_{gt} = \frac{\rho_{h_{gt}}}{\rho_{h_{gt}} + \rho_{a_{gt}} + \rho_c}\overline{h}_{gt} + \frac{\rho_{a_{gt}}}{\rho_{h_{gt}} + \rho_{a_{gt}} + \rho_c}\overline{a}_{gt} > 0, \tag{10}$$

and slope

$$S_{gt} = \frac{\rho_c}{\rho_{h_{gt}} + \rho_{a_{gt}} + \rho_c} > 0. \tag{11}$$

The distributions of human capital and of the additional productivity component vary by gender and field of study, so the linear relationship between c_i and $w_{igt}(c_i)$ may be affected by gender in different ways. In particular, the gender wage gap may have opposite signs across groups.

3.1 Theoretical results

Comparing the male and female intercepts and slopes in equations (10) and (11) yields, in principle, four possible scenarios for the early gender wage gap. Using Assumption 1, we identify the three cases that generate, at least for some values of the CV, an early gender wage gap in favor of men, as observed in the data. As we explain below, these cases depend on whether $\rho_{h_{ft}} \gtrless \rho_{h_{mt}}$ and $\rho_{a_{ft}} \gtrless \rho_{a_{mt}}$.

We consider the following configurations of the linear relationship between wage and CV for male and female prospective workers:

Case 1. $I_{ft} > I_{mt}$ *and* $S_{ft} < S_{mt}$.
Case 2. $I_{ft} < I_{mt}$ *and* $S_{ft} > S_{mt}$.
Case 3. $I_{ft} < I_{mt}$ *and* $S_{ft} < S_{mt}$.

Figure 1a depicts Case 1. From Assumption 1, $I_{ft} > I_{mt}$ holds if the average human capital in field of study t is relatively more informative than the average additional component of productivity ($\rho_{h_{gt}} > \rho_{a_{gt}}\, \forall g$), thus pushing the intercept of females higher than that of males. In addition, from (11), $S_{ft} < S_{mt}$ requires:

$$\rho_{h_{ft}} + \rho_{a_{ft}} > \rho_{h_{mt}} + \rho_{a_{mt}}.$$

In general, a higher slope indicates lower precision in the combined gender-related signals (i.e., $\rho_{h_{gt}} + \rho_{a_{gt}}$ small relative to ρ_c). Thus, if the slope is higher for men than for women, the combined gender-related signals are less precise for men than for women; equivalently, the joint distribution of GPA and the additional productivity component is more dispersed among men. In this case, a strong CV carries relatively more informational weight for men, raising their expected productivity and, consequently, their wages. Figure 1a shows that, if Case 1 holds, a gender wage gap in favor of men arises only when the average CV is sufficiently high—namely, above the intersection point (c_t^*) of the two lines. In that region, the limited quality of the male public signal makes a high CV appear idiosyncratic (i.e., informative about individual productivity rather than group attributes), so that, for the same CV level ($c_i > c_t^*$), the lower precision of the male public signals shifts greater weight onto the private signal and employers impute higher expected productivity to men than to women, thereby offering men a higher wage.

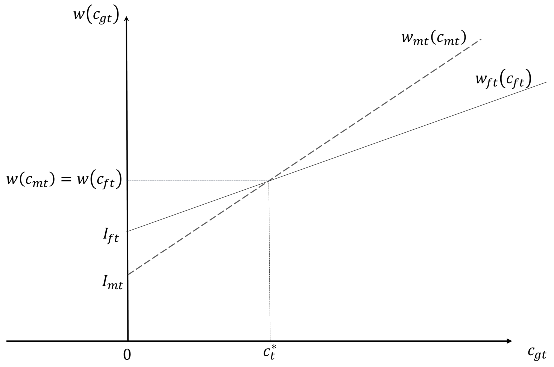
When Case 2 holds, the intercept of male graduates is higher than that of female graduates. Under Assumption 1, this indicates that the average additional component of productivity, a, is relatively more informative than human capital ($\rho_{h_{gt}} < \rho_{a_{gt}}\, \forall g$). In addition, the female slope is now steeper, suggesting that the combined gender-related signals are more precise for men than for women; see Figure 1b. In the figure, the value of the private signal c_i must be sufficiently low—specifically, below c_t^*—for a gender wage gap in favor of men to arise.

Finally, under Case 3, male graduates have both a higher intercept and a steeper slope than female graduates. As illustrated in Figure 1c, employers therefore assign higher wages to men than to women for any positive value of their CV.

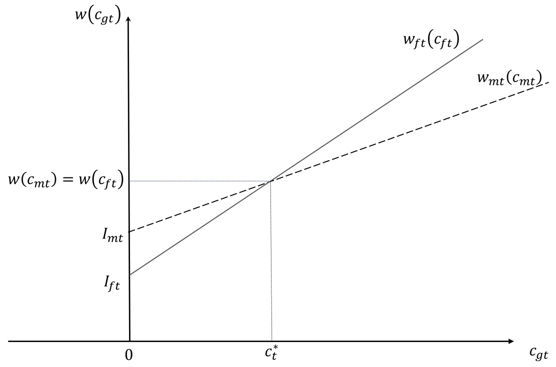
Based on this discussion, we can now summarize the conditions under which our extension of Phelps (1972) predicts an early gender wage gap in favor of men.

Proposition 1. ***Early gender wage gap in favor of men.*** *Let c_t^* denote the CV level at which male and female graduates in the same field of study t receive the same wage offer.*
Then, an early gender wage gap in favor of men can be observed:

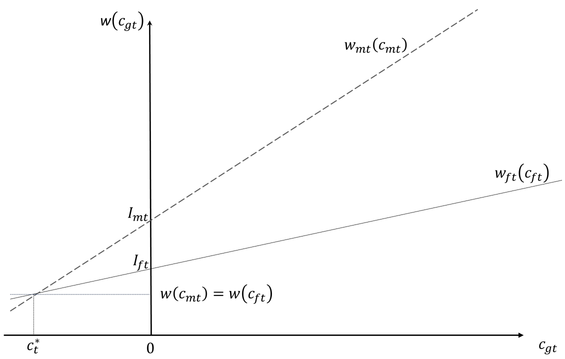
- *when $c \geq c_t^*$ in Case 1.*



(a) Relationship between the expected wage and the CV for female and male graduates when Case 1 holds.



(b) Relationship between the expected wage and the CV for female and male graduates when Case 2 holds.



(c) Relationship between the expected wage and the CV for female and male graduates when Case 3 holds.

Figure 1: Expected wages as a function of the CV, c_{gt}, under the three cases which, for at least some values of the CV, generate an early gender wage gap in favor of men, as observed in the data.

- *when $c < c_t^*$ in Case 2.*
- *always in Case 3.*

Note that, if we consider the full sample of graduates and thus abstract from the field of study, the proposition holds with t omitted. Moreover, as mentioned above, the proposition also holds if the field of study is not a public signal; in this case, again, Proposition 1 can be stated by simply omitting the field of study.

4 Empirical Validation

This section tests whether the theoretical model introduced in Section 3 can account for the early gender wage gap documented in Section 2. Rather than restating descriptive patterns, we draw on the evidence on GPA, wages, mobility intentions, and IT skills presented earlier to calibrate and estimate the model. Specifically, we evaluate whether incorporating mobility intentions (as a proxy for motivation and flexibility) and IT skills (as a proxy for adaptability to evolving work environments and technological change)—improves the explanatory power of the statistical discrimination framework in the full sample of graduates, as well as separately within Economics & Management and within Engineering.

4.1 Data and Descriptive Statistics

We use microdata from the AlmaLaurea Graduate Survey on Italian five-year graduates from the University of Bologna, covering all fields of study and, in particular, Economics & Management and Engineering. Our sample covers the 2015–2022 cohorts observed one year after graduation.[8] We restrict the sample to Italian citizens, younger than 35 at graduation, and employed full-time ($\geq$35 hours per week). Respondents were interviewed shortly before and one year after graduation and reported their employment status and job characteristics. The underlying survey is administered by AlmaLaurea on behalf of the University of Bologna. The University (data owner) granted us access to an anonymized extract provided through the office *APPC – Area Pianificazione, Programmazione e Comunicazione – Settore Programmazione di Ateneo e analisi dati* (University of Bologna).

As mentioned above, we focus on the full sample of graduates across all fields and on two specific fields of study—Economics & Management and Engineering—that differ markedly in gender composition and career trajectories, yet share key labour-market characteristics. In both fields, job candidates face career prospects not only in Italy but also abroad, along with a relatively high probability of employment one year after graduation.

Recall that our main variables include standard measures of human capital as well as the two productivity-relevant attributes. Mobility intentions are captured by the survey question "Availability to work abroad," coded from 1 to 5. *IT skills* are derived from a battery of eleven self-assessed items in the AlmaLaurea questionnaire, which asks graduates to rate their knowledge. Responses are reported on a five-point scale (none, limited, fair, good, excellent). Following the procedure outlined in Section 2, we construct a dummy for each item equal to one if the respondent reports *good* or *excellent*

[8] AlmaLaurea also surveys graduates three and five years after graduation, but those outcomes may reflect further human capital accumulation, job-specific experience, and career dynamics. Early-career wage data collected one year after graduation are better suited to calibrate a statistical discrimination model in which human capital serves as a key signal of productivity.

proficiency. The unweighted sum across the eleven items yields a continuous index ranging from 0–11, which we then normalize into quintiles to facilitate comparability with other covariates. The resulting categorical variable, $IT\ skills_i$, serves as our measure of technological competence.

Tables 4 and 5 report summary statistics for graduates in Economics & Management and Engineering. Engineering graduates earn higher wages and include a lower share of women, whereas Economics & Management graduates display a more balanced gender composition and lower wages. GPA levels are similar across fields (both around 27/30), with Engineering only slightly higher on average, and foreign-language certification rates are also comparable. Mobility intentions are likewise similar, while IT skills are stronger among Engineering graduates. Similar patterns hold in the full sample of University of Bologna graduates, whose summary statistics are reported in Table A.2 in Appendix A.

Tables 1 and 3 in Section 2 show that gender gaps in academic performance, early wages, willingness to work abroad, and IT skills extend beyond specific fields and follow a clear pattern. Women achieve better academic outcomes but report lower willingness to work abroad and lower IT skills (except in Economics & Management, where no gender difference in IT skills is observed); moreover, among employed graduates, women earn less one year after graduation. Taken together, these facts suggest that early wage differences may be consistent with a role for mobility intentions and IT skills as productivity-relevant attributes, alongside candidates' human capital.

Table 4: Summary Statistics for graduates in Economics & Management

Variable	Mean	Std. Dev.	Min	Max	Obs.
Female	0.46	0.50	0.00	1.00	4120
Diploma Grade (60–100)	82.33	11.49	60.00	100.00	4039
GPA (18–30)	26.74	2.26	19.54	30.00	4120
Foreign language	0.14	0.35	0.00	1.00	4120
Availability to work abroad	3.75	1.08	1.00	5.00	3876
IT Skills	2.15	1.16	1.00	5.00	4120
Hours worked weekly	42.72	4.55	37.00	63.00	4120
Monthly wage	1427.05	434.03	200.00	4250.00	3959
Observations					4120

Notes: The table reports summary statistics for graduates in Economics & Management from the University of Bologna (2015–2022) who were employed full-time one year after graduation. The sample excludes foreign-born individuals and those older than 35 at graduation. Diploma grades are on a 100-point scale, GPA on a 30-point scale, and monthly wages are expressed in euros. Willingness to work abroad and IT skills range from 1 to 5, while foreign-language proficiency is a binary indicator. The number of observations for monthly wages is lower because the wage question in the AlmaLaurea survey is not mandatory.

Table 5: Summary Statistics for graduates in Engineering

Variable	Mean	Std. Dev.	Min	Max	Obs.
Female	0.23	0.42	0.00	1.00	4862
Diploma Grade (60–100)	85.44	11.01	60.00	100.00	4808
GPA (18–30)	26.95	2.15	19.00	30.00	4862
Foreign language	0.14	0.35	0.00	1.00	4862
Availability to work abroad	3.86	1.00	1.00	5.00	4722
IT Skills	2.90	1.46	1.00	5.00	4862
Hours worked weekly	43.05	3.84	37.00	63.00	4862
Monthly wage	1496.07	369.46	200.00	4250.00	4704
Observations					4862

Notes: The table reports summary statistics for Engineering graduates from the University of Bologna (2015–2022) who were employed full-time one year after graduation. The sample excludes foreign-born individuals and those older than 35 at graduation. Diploma grades are on a 100-point scale, GPA on a 30-point scale, and monthly wages are expressed in euros. Willingness to work abroad and IT skills range from 1 to 5, while foreign-language proficiency is a binary indicator. The number of observations for monthly wages is lower because the wage question in the AlmaLaurea survey is not mandatory.

4.2 Calibration

In this section, we calibrate the parameters of the theoretical model to evaluate its predictive performance.

Starting from equation (7) and recalling that innate ability has zero mean, we obtain the expression for the average CV, $\bar{c}_{gt}$, for each gender g and field of study t:

$$\bar{c}_{gt} = \bar{h}_{gt} + \bar{a}_{gt}, \tag{12}$$

where $\bar{h}_{gt}$ denotes average human capital and $\bar{a}_{gt}$ the average of the additional productivity traits in the field of study t. Note that $\bar{h}_{gt}$ and $\bar{a}_{gt}$ are proxied by GPA and willingness to work abroad or IT skills by gender and field of study, respectively, and are reported in Tables 1 and 3.

The second step is to use equations (10) and (11) to compute the intercept and slope of equation (9). This allows us to identify the threshold c_t^*, i.e. the CV level at which expected wages for men and women are equal within a field of study, and to compare it with the average level of the CV by gender and field of study, $\bar{c}_{gt}$. Recall that, from Proposition 1, the model correctly predicts the gender wage gap observed in the data if $\bar{c}_{gt}$ is larger (lower) than c_t^* in Case 1 (Case 2), and if c_t^* is negative in Case 3.

To isolate the specific role of the productivity-relevant attribute in explaining the gender wage gap, we contrast two specifications of the model. We first compute c_t^* and

$\bar{c}_{gt}$ when productivity is inferred *only* from the group identity and the noisy signal of human capital, proxied by GPA. This corresponds to the standard formulation of Phelps (1972), in which the terms a and a_i do not appear in equations (4) and (7), respectively. We then compute c_t^* and $\bar{c}_{gt}$ in our extension, where the productivity-relevant attribute is either willingness to work abroad or IT skills. Comparing each augmented version with the baseline allows us to test whether accounting for these additional attributes enhances predictive accuracy and better explains the observed gender asymmetries in early labor market outcomes. In all cases, R^2 is used to obtain a proxy for the unobserved idiosyncratic information contained in the graduates' CV.

The three panels of Table 6 summarize the model parameters for the full sample and for the two fields of study. Within each field and for each gender, we report the average (Mean) and variance (Variance) of three indicators: GPA (in quintiles), availability to work abroad (Abroad, on a 1–5 scale), and IT skills (in quintiles). We also include the signal precision parameter ρ_g, $g \in \{m, f\}$, calculated as the inverse of the variance. Note that, in Panel (c), the field of study is not relevant, and the signal precision parameters correspond to ρ_{h_g} and ρ_{a_g}. In the other two panels, they measure instead $\rho_{h_{gt}}$, and $\rho_{a_{gt}}$. In the last column of Table 6, we report the value of $1-R^2$ obtained from models estimated (i) using only GPA in the first row of each panel, (ii) including both GPA and willingness to work abroad in the second row of each panel, and (iii) including GPA and IT skills in the third row.[9] The value $1-R^2$ serves as a proxy for the parameter ρ_c, capturing residual uncertainty in the productivity signal after accounting for observed characteristics.

In line with Table 1, across both fields of study and in the full sample, female graduates have higher GPAs than male graduates, indicating greater academic performance among women. By contrast, as shown in Table 3, men report higher willingness to work abroad and, except in Economics & Management, stronger IT skills.

Looking at the dispersion of these distributions, we also find gender differences. For GPA, women exhibit slightly higher precision than men across all groups, implying a more concentrated distribution around higher academic performance ($\rho_{h_{ft}} > \rho_{h_{mt}}$ in the two fields and overall), especially in Engineering. By contrast, the precision in willingness to work abroad is lower among women ($\rho_{a_{ft}} < \rho_{a_{mt}}$ in the two fields and overall), with the gap particularly pronounced in Economics & Management, indicating greater heterogeneity in mobility preferences within the female group. A different pattern emerges for IT skills: women display higher precision than men across all samples ($\rho_{s_{ft}} > \rho_{s_{mt}}$), suggesting a more tightly clustered distribution of technological competencies even when male averages are higher. Taken together, these results show that gender differences arise not only in

[9]The R-squared value is obtained from OLS regressions with monthly wage as dependent variable and gender, diploma grade, GPA, hours worked, foreign languages spoken, and dummies for already working before graduation and internship as explanatory variables, plus fixed effects for job sector, graduation year, and social class.

Table 6: Model inputs by gender and field: mean, variance, and signal precision for GPA, willingness to work abroad, and IT skills.

Panel a): Economics & Management

	Males			Females			
Item	Mean	Variance	ρ_m	Mean	Variance	ρ_f	$1-R^2$
GPA (quintile)	3.8204	1.3163	0.7597	3.9318	1.2748	0.7845	0.908
Abroad (1–5)	3.9310	1.0853	0.9214	3.5551	1.1985	0.8344	0.903
IT skills (quintile)	2.8766	1.7824	0.5610	2.9159	1.5546	0.6433	0.908

Panel b): Engineering

	Males			Females			
Item	Mean	Variance	ρ_m	Mean	Variance	ρ_f	$1-R^2$
GPA (quintile)	3.8868	1.2460	0.8026	4.1752	0.9342	1.0704	0.911
Abroad (1–5)	3.8981	0.9805	1.0199	3.7274	1.0571	0.9460	0.902
IT skills (quintile)	3.6133	2.0235	0.4942	3.3785	1.7738	0.5638	0.907

Panel c): All Fields

	Males			Females			
Item	Mean	Variance	ρ_m	Mean	Variance	ρ_f	$1-R^2$
GPA (quintile)	3.8024	1.3070	0.7651	3.9701	1.1325	0.8830	0.922
Abroad (1–5)	3.8770	1.0856	0.9211	3.6071	1.2086	0.8274	0.921
IT skills (quintile)	3.0757	2.2739	0.4398	2.6819	1.9578	0.5108	0.922

Notes: The table reports the mean, variance, and implied signal precision (ρ_g) of GPA, willingness to work abroad, and IT skills—by gender and field of study—for use in calibrating the statistical discrimination model. The final column reports $1-R^2$, which serves as a proxy for the precision of the idiosyncratic component of the CV signal (ρ_c). These inputs are used to generate predictions under the baseline (GPA only) and augmented (GPA+Abroad, GPA+IT skills) model specifications.

mean levels but also in their dispersion, which matters for the model's predictions because both the mean and the precision directly affect signal weights and, consequently, the contribution of each component to expected productivity.

Table 7: Estimated intercepts and slopes of the wage–CV relationship by gender and field, under different model specifications.

Panel a) Economics & Management						
Model's controls	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
Intercept	1.7403	1.8224	2.5248	2.3993	2.0264	2.1235
Slope	0.5445	0.5365	0.3494	0.3581	0.4074	0.3888
Panel b) Engineering						
Model's controls	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
Intercept	1.8204	2.2556	2.6042	2.7396	2.2258	2.5082
Slope	0.5316	0.4598	0.3311	0.3091	0.4116	0.3569
Panel c) All Fields						
Model's controls	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
Intercept	1.7244	1.9422	2.4856	2.4664	2.0038	2.1053
Slope	0.5465	0.5108	0.3532	0.3500	0.4335	0.3981

Notes: The table reports estimated intercepts and slopes of the linear wage–CV relationship derived from the statistical discrimination model, separately by gender and field of study. Values are shown for the baseline specification (GPA only) and for the model augmented with willingness to work abroad or IT skills. These parameters determine the predicted gender wage gap under each scenario.

Using the information in Table 6, we calibrate the average CVs, $\bar{c}_{gt}$, defined in equation (12). These values are reported in Table 8, in the first row of each panel. Panel a) presents results for graduates in Economics & Management, panel b) for Engineering, and panel c) for the full sample including all fields. Specifically, the column "GPA" in Table 8 shows the average $\bar{c}_{gt}$ by gender when only human capital is considered, as in the standard statistical discrimination framework *à la* Phelps (1972). The columns "GPA + Abroad" and "GPA + IT skills" display the average $\bar{c}_{gt}$ obtained from our extended model when mobility intentions and IT skills, respectively, are incorporated alongside human capital.

To illustrate the procedure, consider a male graduate in Economics & Management. From Table 6, we know that his average GPA in quintile is 3.8204. In the baseline framework *à la* Phelps (1972), this is the sole determinant of productivity, so the corresponding average CV equals 3.8204 (see the first entry in Table 8). In our extended model, however, productivity also depends on willingness to work abroad, reported in Table 6 as 3.9310. According to equation (12), the resulting average CV is therefore $\bar{c}_{mEM} = 3.8204 + 3.9310 = 7.7514$, where $\bar{c}_{mEM}$ denotes average male CV in Economics & management. The same procedure, using information on IT skills from Table 6, is applied to obtain the values reported in the last column, "GPA + IT skills".

Table 8: Average CV values ($\bar{c}_{gt}$) and intersection thresholds (c_t^*) by gender and field under different model specifications.

Panel a) Economics & Management

	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
$\bar{c}_{gEM}$	3.8204	3.9318	7.7514	7.4869	6.697	6.8477
c^*_{EM}	10.263		14.425		5.2204	

Panel b) Engineering

	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
$\bar{c}_{gE}$	3.8868	4.1752	7.7849	7.9026	7.5001	7.5537
c^*_{E}	6.0613		6.1545		5.1627	

Panel c) All Fields

	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
$\bar{c}_{g}$	3.8024	3.9701	7.6794	7.5772	6.8781	6.652
c^*	6.1008		-6.0000		2.8672	

Notes: The table reports average CV values ($\bar{c}_{gt}$) and the corresponding intersection thresholds (c_t^*) derived from the wage–CV functions in the statistical discrimination model. Values are shown for the baseline specification (GPA only) and for the augmented models including willingness to work abroad or IT skills. Comparing $\bar{c}_{gt}$ to c_t^* determines whether the model predicts a gender wage gap in each field and specification.

The next step is to calibrate the values of c_t^*, defined by the intersection of equations (9) for male and female graduates. These values are reported in the second row of each panel of Table 8. To compute c_t^* we use information contained in Table 7. The latter shows the estimated intercepts and slopes from equations (10) and (11) for the two fields of study and the full sample, separately for men and women. As Table 8, Table 7 consider the three specifications: the baseline model, which includes only GPA as a proxy for human capital (column "GPA"); the model augmented with mobility intentions, which also incorporates willingness to work abroad as a component of productivity (column "GPA + Abroad") and the model augmented with IT skills, where digital competencies are added as an additional productivity component (columns "GPA + IT skills").

Let us start with Economics & Management and consider column "GPA" of Table 7. Here, female graduates have a higher intercept (1.8224 vs. 1.7403) and a slightly lower slope (0.5365 vs. 0.5445) than male graduates. This configuration is consistent with Case 1 in the theoretical model. By Proposition 1, in this case a gender wage gap favoring men emerges if male and female average CVs, $\bar{c}_{mEM}$ and $\bar{c}_{fEM}$, are both larger than the threshold $c^*_{EM} = 10.263$, where the subscript EM indicates Economics & Management.[10] However, as reported in Table 8, both average CVs are lower than c^*_{EM}. Therefore, a model that considers only human capital would predict the opposite of what is empirically observed: a wage gap in favor of women rather than men.

Now, let us consider the extension "GPA + Abroad" in Economics & Management. From Table 7 women display a lower intercept (2.3993 vs. 2.5248) and a slightly higher slope (0.3581 vs. 0.3494) than men. This configuration corresponds to Case 2. By Proposition 1, a gender wage gap in favor of men should emerge if the average CVs of men and women are lower than the threshold for the "GPA + Abroad" specification, $c^*_{EM} = 14.425$. As reported in Table 8, both average CVs indeed are lower than this threshold; where $\bar{c}_{mEM} = 3.8204{+}3.9310 = 7.7514$ and $\bar{c}_{fEM} = 3.9318{+}3.5551 = 7.4869$. Hence, the model augmented with willingness to work abroad is consistent with the empirical evidence and explains the emergence of a gender wage gap in favor of men.

Let us consider IT skills. From column "GPA + IT skills" of Table 7 men display a lower intercept (2.0264 vs. 2.1235) and a higher slope (0.4074 vs. 0.3888) than women, corresponding to Case 1. As shown in column "GPA + IT skills" of Table 8, average CVs ($\bar{c}_{mEM} = 3.8204 + 2.8766 = 6.697$ and $\bar{c}_{fEM} = 3.9318 + 2.9159 = 6.8477$) are now larger than the new intersection $c^*_{EM} = 5.2204$, and thus the model correctly predicts a wage gap in favor of men. Thus, in Economics & Management, both mobility intentions and IT skills help reconcile the empirical evidence with the theoretical predictions.

Next, we turn to Engineering. In this field, the relationship between intercepts and slopes remains unchanged when mobility intentions or IT skills are included: female graduates have a higher intercept and a lower slope than male graduates in all three specifications. Consequently, Case 1 always holds and, by Proposition 1, average CVs must be larger than c^*_t for a gender wage gap in favor of men to emerge. As shown in Table 8, the specification with "GPA" only would predict a wage gap in favor of female graduates. It is the inclusion of willingness to work abroad or IT skills that accounts for the observed gender wage gap in favor of male graduates.

Finally, we consider the full sample including all fields, reported in panel (c) of Table 8. In the baseline specification with "GPA" as the only regressor, Table 7 shows that female graduates have a higher intercept (e.g., 1.9422 vs. 1.7244) and a slightly lower slope

[10] The intersection point between male and female wage profiles is obtained by equating the two linear predictions, $1.8224 + 0.5365\bar{c}_t = 1.7403 + 0.5445\bar{c}_t$, and solving for $\bar{c}_t$.

(0.5108 vs. 0.5465) than male graduates, which corresponds to Case 1. According to Proposition 1, this specification would imply an early gender wage gap in favor of women if c^* were lower than both $\bar{c}_m$ and $\bar{c}_f$. However, Table 8 shows that the opposite is true. Therefore, the specification with "GPA" only cannot account for the observed early gender wage gap.

Moving to the specification "GPA + Abroad" in the full sample, Table 7 shows that Case 3 holds, as both the intercept and the slope are higher for male candidates. In this case, we expect the intersection point c^* to be negative and a gender wage gap in favor of men to arise for all values of c, which is confirmed in Table 8.

In the specification "GPA + IT skill," Table 7 shows that female graduates have a higher intercept and a slightly lower slope than male graduates, corresponding to Case 1. According to Proposition 1, this specification implies an early gender wage gap in favor of women if c^* is lower than both $\bar{c}_m$ and $\bar{c}_f$, which is indeed the case, as shown in Table 8. Therefore, as in the two field-specific analyses, extending the model to incorporate either willingness to work abroad or IT skills aligns theoretical predictions with the empirical evidence of a gender wage gap favoring men in the aggregate sample.

These calibration findings suggest that the statistical discrimination model can account for the emergence of an early gender wage gap in favor of men when employers evaluate productivity-relevant attributes such as willingness to work abroad or IT skills in addition to graduates' human capital. In particular, employers may combine information on acquired human capital at university (e.g. GPA by gender and field of study) with gender-disaggregated descriptive statistics on other relevant traits, and use these extended group-level signals when forming expectations about individual productivity.

4.3 Empirical Validation

In this subsection, we assess whether the mechanisms highlighted in our revisited model of statistical discrimination are borne out in the data. In the previous section, we calibrated the model with a productivity-relevant trait—either willingness to work abroad or IT skills. Now, we estimate simple wage regressions in which we first recover the raw (or conditional on basic controls) gender wage gap one year after graduation and then examine how it changes once each trait is included among the regressors. This allows us to test whether systematic (gender) differences in mobility intentions and IT skills account for part of the observed gender wage differential. If their inclusion reduces the raw gap, our extended Phelps framework is not only consistent with the calibration exercise, but also supported by the empirical evidence on early-career wages, both in the full sample and within Economics & Management and Engineering.

We estimate a simple OLS model where the dependent variable is the monthly wage one year after graduation:

$$Wage_i = \alpha_0 + \alpha_1 Female_i + \alpha_2 Abroad_i + \Gamma_i + \Lambda_i + \epsilon_i, \tag{13}$$

where $Female_i$ is a dummy equal to one for women, and $Abroad_i$ captures the respondent's reported willingness to work abroad on a $1-5$ scale.[11]

We also estimate the following model:

$$Wage_i = \alpha_0 + \alpha_1 Female_i + \alpha_2 ITskills_i + \Gamma_i + \Lambda_i + \epsilon_i, \tag{14}$$

where $ITskills_i$ captures the respondent's information-technology proficiency again on a $1-5$ scale.[12]

These specifications also includes two sets of controls. Γ_i represents environmental controls, such as the year of graduation and the sector of employment. Λ_i denotes individual-level characteristics, including GPA, whether the graduate was already employed before completing the degree, high-school diploma grade, geographic mobility at the time of high-school graduation (same vs. different region as the university), parental education (as a proxy for social background), weekly hours worked, participation in internships during studies, and indicator for foreign language certification. In the case of the full sample results, we also include the field of study FE.

In this framework, the coefficient α_1 measures the gender wage gap after conditioning on individual and environmental traits. The coefficient α_2 captures the effect of the productivity–relevant characteristic—either willingness to work abroad or IT skills—on wages one year after graduation.

As shown in Table 9, the gender wage gap one year after graduation is sizeable and statistically significant across both fields of study and in the full sample. The gap is smallest in Economics & Management (about €80 per month) and largest in Engineering (about €107), both close to the overall average difference of roughly €120 in the full sample. These results confirm that gender disparities in earnings emerge very early in professional careers, despite comparable educational attainment.
Including the variable *Abroad*, which captures willingness to work abroad, reduces the estimated gender wage gap—to about €69 in Economics & Management, €104 in Engineering, and €117 in the full sample—indicating that systematic gender differences in mobility intentions contribute meaningfully to the observed wage differential. Because the coefficient on *Abroad* is positive and statistically significant across specifications, this variable is remunerated in the labour market. This pattern is consistent with interpreting willingness to work abroad as a productivity-related trait—reflecting geographic flexibility, readiness to accept a broader set of job opportunities, and ambition—that employers value and reward. Accordingly, once this remunerated attribute is accounted for, part of

[11] See Section 2 for details on how this variable is constructed.
[12] See again Section 2 for additional details.

Table 9: Wage regressions by field of study and for the full sample: impact of willingness to work abroad.

	Economics & Management		Engineering		All Fields	
Column	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**Dependent variable: monthly wage**					
Female	-80.038***	-69.845***	-107.737***	-103.881***	-120.305***	-116.830***
	(14.105)	(14.278)	(12.735)	(12.678)	(6.585)	(6.623)
Abroad	-	33.258***	-	35.455***	-	13.375***
		(6.669)		(5.357)		(2.742)
Observations	3,601	3,584	4,466	4,447	21,624	21,480
R-squared	0.091	0.097	0.089	0.098	0.157	0.159
Env. Controls	YES	YES	YES	YES	YES	YES
Ind. Controls	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses. The table reports OLS estimates of monthly wages one year after graduation. Odd-numbered columns include only the female dummy (raw gender wage gap), while even-numbered columns additionally include willingness to work abroad. All specifications control for individual characteristics and environmental factors (graduation year and job-sector fixed effects). Data: AlmaLaurea, University of Bologna graduates, 2015–2022. *** p<0.01, ** p<0.05, * p<0.1.

the raw gender wage gap mechanically shrinks, as some of the wage premium associated with mobility intentions was previously attributed to gender.

Table 10 reports the regression results when IT skills are included as an explanatory variable. The first row of the table reports the same regression coefficients as Table 9.

Table 10: OLS wage regressions by field of study and for the full sample including IT skills.

	Economics & Management		Engineering		All Fields	
Column	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**monthly wage**					
Female	-80.038***	-79.969***	-107.737***	-101.973***	-120.305***	-119.302***
	(14.105)	(14.098)	(12.735)	(12.805)	(6.585)	(6.593)
IT skills	-	7.583	-	18.205***	-	7.149***
		(5.855)		(4.002)		(2.131)
Observations	3,601	3,601	4,466	4,466	21,624	21,624
R-squared	0.091	0.092	0.089	0.093	0.157	0.158
Env. Controls	YES	YES	YES	YES	YES	YES
Ind. Controls	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses. The table reports OLS estimates of monthly wages one year after graduation. Odd-numbered columns include only the female dummy (raw gender wage gap), while even-numbered columns additionally include IT skills. All specifications control for individual characteristics and environmental factors (graduation year and job-sector fixed effects). Data: AlmaLaurea, University of Bologna graduates, 2015–2022. *** p<0.01, ** p<0.05, * p<0.1.

Turning to the coefficient on IT skills, we find substantial heterogeneity across fields. In Economics & Management, the gender wage gap decreases only marginally, while the coefficient on IT skills remains positive but fails to reach statistical significance. Recall that, in our sample, there is no significant gender difference in the mean level of IT skills in this field (Table 3). Nonetheless, in line with our calibration, which relies on the values of ρ_g reported in Table 6, including IT skills among the controls still produces a small reduction in the estimated gender wage gap in this field. By contrast, in Engineering, IT skills are associated with a statistically significant wage premium: controlling for IT skills reduces the raw gender wage gap by about €6 per month. In the full sample, the corresponding effect is small—around €1 per month—but remains positive and statistically significant.

Our empirical analysis suggests that the contribution of these productivity–relevant attributes to early wages differs across fields and in the full sample. Mobility intentions play a central role both within the two fields of study and in the aggregate, while IT skills significantly improve earnings prospects and help explain part of the gender wage gap only in Engineering, with no significant effect in Economics & Management and only a small effect in the full sample.

More generally, willingness to work abroad seems a stronger and more consistent proxy for the productivity-related attribute in our extended Phelps framework.

5 Concluding remarks

A gender wage gap emerges immediately at labour-market entry despite women outperforming men in academic achievement. This pattern is difficult to reconcile with standard human-capital explanations and motivates a return to the statistical discrimination framework rooted in Phelps (1972). In contemporary labour markets, large-scale descriptive statistics by gender, field of study, institution, and cohort are routinely available through administrative data, graduate surveys, and institutional dashboards. This informational environment makes our extension of the Phelps framework particularly relevant, as employers can draw not only on aggregate measures of academic performance but also on group-level statistics for additional productivity-related attributes.

We extend the model to include productivity-relevant traits beyond human capital—specifically mobility intentions and IT skills—that vary between men and women and across fields of study. In our sample, willingness to work abroad and IT competencies are more prevalent among men.

Employers observe noisy individual CVs as private signals and rely on gender- and field-specific distributions as public signals. Through this mechanism, group-level information shapes expected productivity, making differences in mobility intentions and IT skills relevant for wage setting even when women's academic performance is higher.

Using AlmaLaurea data, we calibrate the model for the full sample and separately for Economics & Management and Engineering. Human capital alone cannot generate the observed male wage premium at entry. Incorporating mobility intentions or IT skills produces predictions that closely match the empirical gaps.

Complementary regression analysis supports this mechanism: adding mobility intentions or IT skills to simple wage regressions reduces the raw gender gap in patterns consistent with the calibrated model. Specifically, mobility intentions seem to be a key driver of the observed gender wage gap in both fields and in the aggregate, while IT skills matter primarily in Engineering, where gender differences in these competencies are more pronounced.

Taken together, the evidence suggests that early gender wage differentials arise not only from differences in academic characteristics but also from employers' use of group-level information when evaluating other components of productivity.

Women excel in academic performance, yet the labour market seems to reward other traits more heavily—for example, willingness to work abroad and IT competencies, which are more prevalent among men in our sample. If these attributes significantly shape employers' productivity expectations, reducing early gender wage gaps requires policies that expand women's opportunities and incentives to acquire and clearly signal these market-valued traits. Relevant interventions include promoting international mobility for female graduates, strengthening access to IT-intensive training (especially in non-STEM fields), and improving the visibility and standardisation of such competencies in hiring processes. On the employer side, recruitment practices that place less weight on coarse group statistics—such as structured skill assessments, standardised interviews, and clearer certification of IT and mobility experiences—may reduce statistical discrimination. Future research could explore additional attributes—such as willingness to work irregular hours, openness to specific job tasks, or preferences for certain work environments—that may play a more important role in fields where mobility intentions and IT skills are less salient.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGTP 5 to improve language and readability, with caution. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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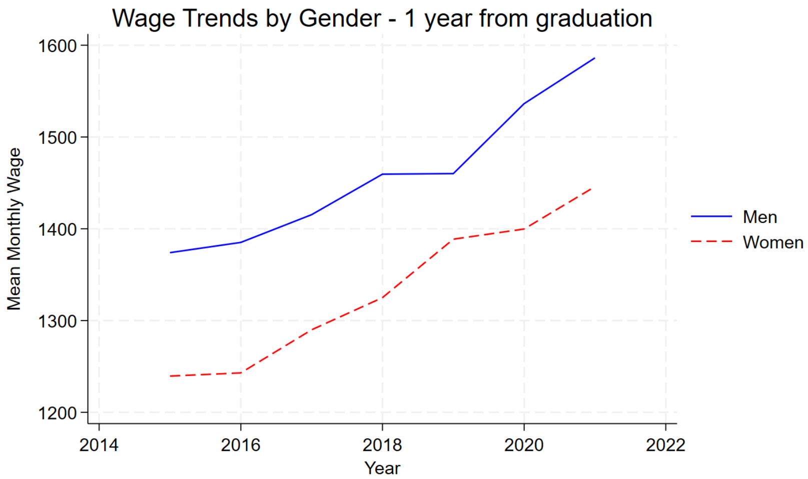
A Additional Figures and Tables

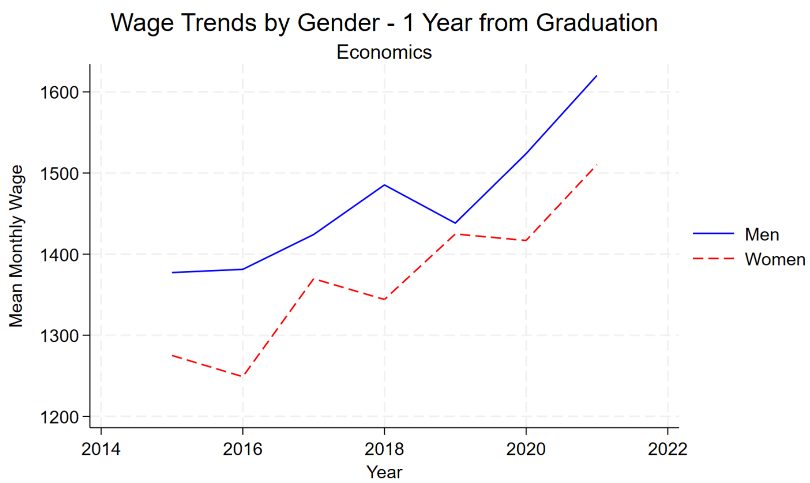
In Figures A.1-A.3, we present wage trends one year after graduation by graduation year and gender for the whole sample and the two fields of study.

Figure A.1: Wage and Gender, all fields of study



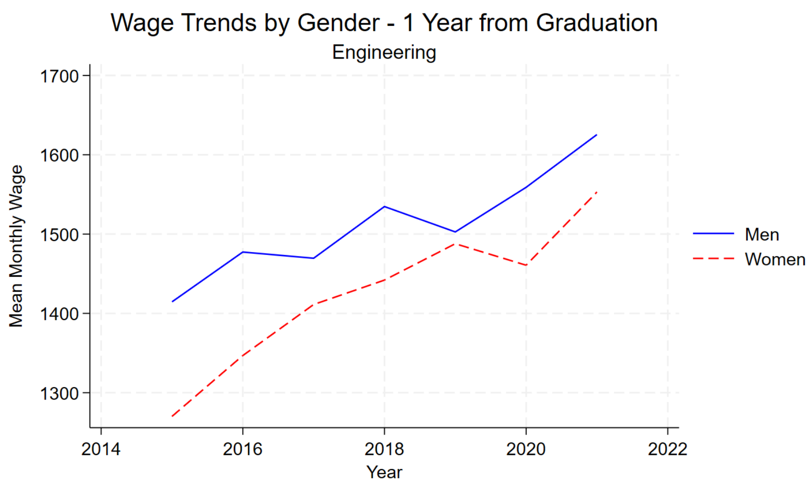
Note: Trends in wages by graduation year and gender in the full sample (all fields of study). Data come from AlmaLaurea respondents who graduated from the University of Bologna between 2015 and 2022. For the 2022 cohort, wage information one year after graduation is not yet available.

Figure A.2: Wage and Gender – Economics & Management



Note: Trends in wages by graduation year and gender for graduates in *Economics & Management*. Data come from AlmaLaurea respondents who graduated from the University of Bologna between 2015 and 2022. For the 2022 cohort, wage information one year after graduation is not yet available.

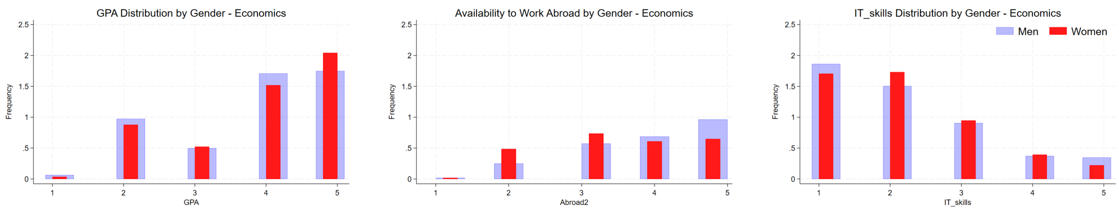
Figure A.3: Wage and Gender – Engineering



Note: Trends in wages by graduation year and gender for graduates in *Engineering*. Data come from AlmaLaurea respondents who graduated from the University of Bologna between 2015 and 2022. For the 2022 cohort, wage information one year after graduation is not yet available.

Figure A.4: Comparison of the quintile distributions of GPA, willingness to work abroad, and IT skills by gender across fields of study.

(a) **All fields**



(b) **Economics & Management**

(c) **Engineering**

Table A.1: Correlation between willingness to work abroad and IT skills by gender and field of study.

Field of study and gender	Correlation coefficient	p-value
All fields (Men)	0.0953	0.0000***
All fields (Women)	0.1282	0.0000***
Economics and Man. (Men)	0.1020	0.0000***
Economics and Man. (Women)	0.1316	0.0000***
Engineering (Men)	0.0952	0.0000***
Engineering (Women)	0.1055	0.0004***

Notes: Pairwise correlations between willingness to work abroad and IT skills, reported separately by gender and field of study. All coefficients are positive and statistically significant, though small in magnitude, indicating only a modest association between the two attributes. Data: AlmaLaurea, University of Bologna graduates, 2015–2022. *** p<0.01.

Table A.2 below reports summary statistics for the full sample of five-year laureates from the University of Bologna between 2015 and 2022.

Table A.2: Summary Statistics for the Full Sample of Graduates

	Mean	Std. Dev.	Min	Max	Obs.
Female	0.51	0.50	0.00	1.00	24060
Diploma grade (60–100 scale)	81.93	11.70	60.00	100.00	23720
GPA (18–30 scale)	26.88	2.10	18.60	30.00	24058
Foreign language	0.13	0.34	0.00	1.00	24060
Availability to work abroad	3.74	1.08	1.00	5.00	22847
IT skills	2.87	1.47	1.00	5.00	24060
Weekly hours worked	42.17	4.63	37.00	63.00	24060
Monthly wage (€)	1396.50	447.66	200.00	4250.00	23137
Observations	24060				

Notes: The table reports summary statistics for all University of Bologna graduates (2015–2022) employed full-time one year after graduation. The sample excludes foreign-born individuals and those older than 35 at graduation. Diploma grades are on a 100-point scale, GPA on a 30-point scale, and monthly wages are in euros. Willingness to work abroad and IT skills range from 1 to 5, while foreign-language proficiency is a binary indicator. The number of observations for monthly wages is lower because the wage question in the AlmaLaurea survey is not mandatory.

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