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Francesca Barigozzi
Natalia Montinari
Giovanni Righetto
Alessandro Tampieri

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Beyond Human Capital: Mobility intentions, IT skills, and the Early Gender Wage Gap*

Francesca Barigozzi[1], Natalia Montinari[1], Giovanni Righetto[1], and Alessandro Tampieri[2]

[1]University of Bologna
[2]University of Modena and Reggio Emilia

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Abstract

In most countries, women systematically outperform men in academic achievement across fields of study. Yet within a year of graduation, they earn less, face lower employment rates, and are more likely to work part-time. If human capital were the sole determinant of pay, this pattern would be difficult to reconcile. We address this puzzle by extending the statistical discrimination framework 'a la Phelps (1972) to include not only human capital but also additional components of productivity, such as IT skills and mobility intentions -the willingness to travel or relocate for work -which might capture candidates' technological proficiency and adaptability. Using rich microdata from the AlmaLaurea survey of master's graduates from the University of Bologna (2015–2022), we show that while human capital alone predicts no gender wage gap in favor of men, combining it with mobility intentions reproduces the early wage disadvantage observed for women in Economics and Engineering. We further show that IT skills -an observable CV trait constructed from multiple IT-skill items- reduce the residual gender wage gap, especially in Engineering. Our findings highlight the importance of complementing human capital with field-specific preference and skill traits to explain—and potentially address—early gender wage gaps.

Keywords: Gender wage gap; statistical discrimination; human capital; mobility intentions; IT skills; field of study; early career outcomes.
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 fields of study, including Economics and Management and Engineering. Yet, just one year after graduation, they already earn lower wages, are less likely to be employed, and more often work part-time. 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 rich microdata from the AlmaLaurea survey of University of Bologna graduates (2015–2022), the study shows that:

- Women outperform men academically, but men report stronger IT skills and greater willingness to work abroad.
- When only human capital is considered, the Phelps' model wrongly predicts a wage advantage for women.
- Once mobility intentions and IT skills are added, the model reproduces the actual gender wage gaps observed in Economics/Management and Engineering.
- Mobility intentions matter in both 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, while IT skills yield higher pay only in Engineering. In both cases, part of the gender wage gap can be traced to these traits, which employers may use as "public signals" 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 in Economics and Management and Engineering should not only focus on equalizing human capital, but also on promoting 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 reinforce disparities that do not reflect true differences in potential.

1 Introduction

A well-documented puzzle in labor economics is that, despite systematically outperforming male peers in academic settings (see Conger and Long, 2010, for the USA; Verbree et al., 2023, for the Netherlands; Carroll, 2023, for the UK), women experience worse labor market outcomes soon after graduation (see, among many others, Bertrand, 2020). In Italy, female students achieve higher grades in both secondary school and university across all fields of study, yet within just one year of entering the labor market, they earn less, have lower employment rates, and are more likely to work part-time (Piazzalunga 2018; Bovini et al. 2024). These disparities arise well before family commitments typically become binding constraints, suggesting that they cannot be fully accounted for by differences in work–life balance choices. If pay were determined solely by human capital, women's superior academic performance would translate into earnings at least equal to, if not higher than, those of men.

How can this pattern be explained? Does human capital yield higher returns for male than for female graduates, or do employers form expectations about candidates' future productivity based on information beyond academic achievement?

A growing literature emphasizes that preferences for job characteristics and other determinants of productivity can influence both labor supply and demand (e.g., Le Barbanchon et al., 2021), helping to explain why women continue to lag behind in labor market outcomes. In this study, we introduce mobility intentions and IT skills as additional components of productivity in a statistical discrimination model and test whether they may help explain the early gender wage gap. Our idea is that when employers observe that an additional trait is systematically distributed differently across male and female job seekers, this trait can complement the public signal they already derive from the gender-specific distribution of human capital.

Additional productivity components and job preferences capture dimensions of productivity beyond traditional human capital that the labor market may reward. These factors can also be field-specific, with their relevance varying across educational backgrounds, occupational contexts, and workplaces. Our main argument is that understanding their role is essential to explain why gender wage gaps emerge unevenly across disciplines. To this end, we focus on two specific traits: mobility intentions and IT skills.

We aim to investigate whether gendered patterns in job seekers' mobility intentions and IT skills help explain the early labor market advantage observed for men. Both components can plausibly be viewed as determinants of productivity, though their relevance may vary across fields of study: mobility intentions capture motivation, flexibility, and willingness to pursue geographically mobile career opportunities, while IT skills reflect adaptability to evolving work environments and technological improvements in the workplace. The literature reviewed below documents systematic gender differences in both dimensions, and it is plausible that employers are aware of these patterns, which serve as a "public signal" evaluated alongside the private signal contained in the candidates' CV.

Recent evidence has shown a gender gap in commuting and geographic mobility, which may influence occupational choices and labor market outcomes. Le Barbanchon et al. (2021)

find that women are less willing to accept jobs involving long commutes, potentially influencing job sorting and wage disparities. Liu and Su (2024) similarly demonstrate that gender differences in mobility tolerance contribute to inequality in job matching and career trajectories. Havet et al. (2021) provide additional evidence that women are less likely to accept jobs requiring substantial commuting distances, even after accounting for family responsibilities and job characteristics. Cortés et al. (2023) further emphasize that gender differences in preferences —particularly regarding job attributes such as flexibility and location— are a major factor in explaining occupational choices, even among students with similar academic performance and labor market expectations. Finally, Abraham et al. (2019) show that, within couples, women are significantly less willing than their male partners to relocate for a new job, even an attractive one. In practice, coupled women may miss out on career-advancing job offers that require moving, thereby hindering their career progression relative to men. These findings highlight the importance of geographic flexibility and job preferences as mechanisms contributing to gender differences in labor market outcomes.

Beyond indicating preferences over job attributes, willingness to relocate for work also serves as a proxy for non-cognitive skills—motivation, ambition, and grit—(Duckworth et al., 2007; Aigner and Cain, 1977; Heckman et al., 2006; Almlund et al., 2011). In particular, willingness to work abroad can reveal persistence and a long-term career orientation, traits the literature associates with higher productivity and improved labor-market outcomes.

Recent evidence also points to the growing importance of IT-related competencies in shaping gender differences in labor market outcomes. Early work by Hargittai (2002) documents that gender gaps persist not only in internet access but also in digital skills, providing foundational evidence that technological competence itself constitutes a key productivity component. Black and Spitz-Öener (2010) show that technological change reshaped the skill content of women's work, with IT-related competencies increasingly driving occupational sorting and productivity. Similarly, Cortés and Goldin (2020) highlight how technological advances can reduce -but do not eliminate- gender wage gaps, underscoring the centrality of IT skills in modern labor markets. Building on this, Bustelo (2019) emphasize that inequalities in digital skills translate directly into wage disparities, particularly penalizing women in occupations where such competencies are highly rewarded. Complementary evidence by Zhang (2024) further shows that the expansion of the digital economy influences gender wage gaps across sectors, reinforcing the notion that IT skills are field-specific productivity components that employers value. These findings suggest that gender differences in IT skills may help explain part of the early career wage gap, especially in disciplines where technological competencies are less embedded in the academic curriculum.

We address this question within a statistical discrimination framework à la Phelps (1972), which provides a suitable setting to explore why women may earn less despite having higher human capital. In such models, employers do not observe candidates' productivity directly; instead, they form expectations based on observable signals that are informative about the distribution of productivity within groups. Specifically, employers rely on the CV as a private signal, and on gender and field of study as public signals, since these convey information about how determinants of productivity are distributed across groups. Standard applications of the Phelps model typically assume productivity depends only on human capital, proxied by GPA and field of study. However, in our dataset, women perform at least as well as men on these dimensions, so the model would predict no gender wage gap—or even an advantage for women. By contrast, when we extend the framework to include additional components such as mobility intentions and IT skills, and when employers believe these traits are positively associated with productivity, gender gaps can emerge. Since men on average display higher willingness to work abroad and stronger IT skills, the model reproduces the empirical patterns observed for recent graduates in Economics and Management and Engineering in Italy. At the same time, the salience of these components is likely field-specific: mobility intentions matter more in disciplines where geographic mobility is rewarded, while IT skills are especially relevant in fields where tasks are technologically intensive and complementary to digital competencies (e.g., Engineering). This extension allows the model to better align with observed heterogeneity across fields.

To validate our theoretical findings, we draw on Almalaurea survey data on master's graduates from the University of Bologna between 2015 and 2022 in two distinct fields of study: Economics and Management, and Engineering. Across the two fields, women outperform men in terms of GPA, suggesting that -if academic performance were the sole determinant of pay- they should earn at least as much as their male peers. Yet, the opposite is observed. Extending the model to include either willingness to work abroad or IT skills improves its explanatory power. If employers expect women to be less willing to accept positions involving relocation or international assignments, and to have on average lower IT skills, they may incorporate this information when forming beliefs about candidates' productivity. Once calibrated with these additional productivity components, the model reproduces the observed gender wage differentials in Economics and Management and in Engineering.

The choice to analyze these two fields separately is motivated by differences in gender composition, gender stereotypes, and the types of students they attract. For example, Engineering remains largely male-dominated and is still widely perceived as a "male" field, with relatively few female students. By contrast, Economics has a balanced gender composition[1]. Moreover, the two fields appeal to students with different preferences, skills, and career aspirations, and they lead to distinct occupational paths with varying opportunities, working conditions, and wage structures. Analyzing them separately allows us to compare groups of graduates who are more internally homogeneous in terms of opportunities and constraints, which is crucial when assessing wage differences one year after graduation. However, the two fields of study also share important similarities: both provide graduates with strong international career prospects and a high likelihood of employment.

The theoretical model builds on the literature on statistical discrimination, pioneered by Arrow (1971) and Phelps (1972).[2] 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

[1] In our sample, female graduates are 23% in Engineering and 46% in Economics and Management.

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

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.

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 showing a considerable decline during this period. Then, they 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 components of productivity, like mobility intentions and IT skills -that may correlate with productivity. Employers, in this framework, form expectations not only from academic performance but also from other components 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 signals into the framework. Our contribution is therefore novel in showing that adding these dimensions allows a Phelps-type model to reproduce the early gender wage gap among recent graduates, while also highlighting that different components matter across fields.

The remainder of the paper is structured as follows. 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 both mobility intentions and IT skills. Section 3 introduces the statistical discrimination model, calibrated using measures of human capital alongside alternative additional components (i.e., mobility intentions and IT skills) of productivity. Section 4 tests whether the theoretical model can account for the early gender wage gap documented and examine, in turn, the role of mobility intentions and IT skills in explaining its magnitude across fields. Section 5 concludes.

2 Empirical Motivation

Before presenting the theoretical framework, we provide descriptive evidence on the early gender wage gap among graduates from the University of Bologna. Our aim is to highlight the empirical puzzle that motivates the extension of the statistical discrimination model.

As explained in the introduction, we focus on Economics and Management and Engineering because they differ markedly in gender composition, stereotypes, and career trajectories, while still offering comparable prospects in terms of international opportunities and employment Table 1 summarizes two stylized facts across Economics and Management, and Engineering.[3] First, women consistently outperform men in terms of academic achievement, with a higher average GPA in the two fields of study considered. Second, despite this advantage, women earn lower wages one year after graduation.

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

Table 1: Motivating Facts: Wages and GPA by Gender and Field of study

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

Notes: The table reports average monthly wages (euros) and GPA on a 30-point scale. Values are shown by gender and field of study. The reported t-tests refer to statistical differences in average monthly wages between male and female graduates. Source: AlmaLaurea survey data, Bologna University graduates, 2015–2022.

These descriptive patterns are difficult to reconcile with a purely human-capital-based explanation of early career outcomes. If wages were determined only by academic performance, women should enjoy a wage premium, not a penalty, given their stronger academic record. Instead, the opposite is observed: women earn less than men at the very beginning of their careers. This points to the importance of additional determinants of productivity beyond human capital.

In addition to human capital, we focus on two sets of components of productivity that can be drawn from a job candidate's CV: mobility intentions and IT skills. Both are derived from the information available in the AlmaLaurea dataset.

First, we measure mobility intentions using the survey question that asks respondents whether they are willing to work abroad. We define

$$Mobility_i = \begin{cases} 1 & \text{if the graduate declares willingness to work abroad,} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

This indicator captures 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 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 given on an ordered scale (none, limited, fair, good, excellent).

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

$$D_{ik} = \begin{cases} 1 & \text{if respondent } i \text{ reports “good” or “excellent” proficiency in area } k, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

We then compute the unweighted sum

$$IT\_skills_i^{continuous} = \sum_{k=1}^{11} D_{ik}, \tag{3}$$

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

$$IT\_skills_i = \text{quintiles}\left(IT\_skills_i^{continuous}\right). \tag{4}$$

This symmetric construction ensures that the two additional components -mobility intentions and IT skills- are treated consistently, allowing us to explore their role in shaping gender wage differentials across fields of study.

Figures 1 and 2 compare GPA (grouped into quintiles), willingness to work abroad (measured on a five-point categorical scale), and IT skills (constructed from self-assessed proficiency and expressed in quintiles) by gender.[4][5] Women systematically report lower willingness to work abroad and weaker IT skills. These divergences, consistent across the two disciplines, suggest that gender wage gaps may be linked less to academic ability and more to differences in job-related preferences and competencies.

[4]The GPA quintiles are defined as: first 18–21, second 22–25, third only 26, fourth 27–28, and fifth 29–30. The mobility question—*Are you willing to work abroad?*—is coded 1 to 5: “Absolutely not”, “More no than yes”, “Neither yes nor no”, “More yes than no”, and “Definitely yes”. IT skills are coded by quintiles of the continuous index described in Section 2.

[5]We use quintiles to harmonize scales across variables and provide a common discrete support for the model calibration performed later in the paper.

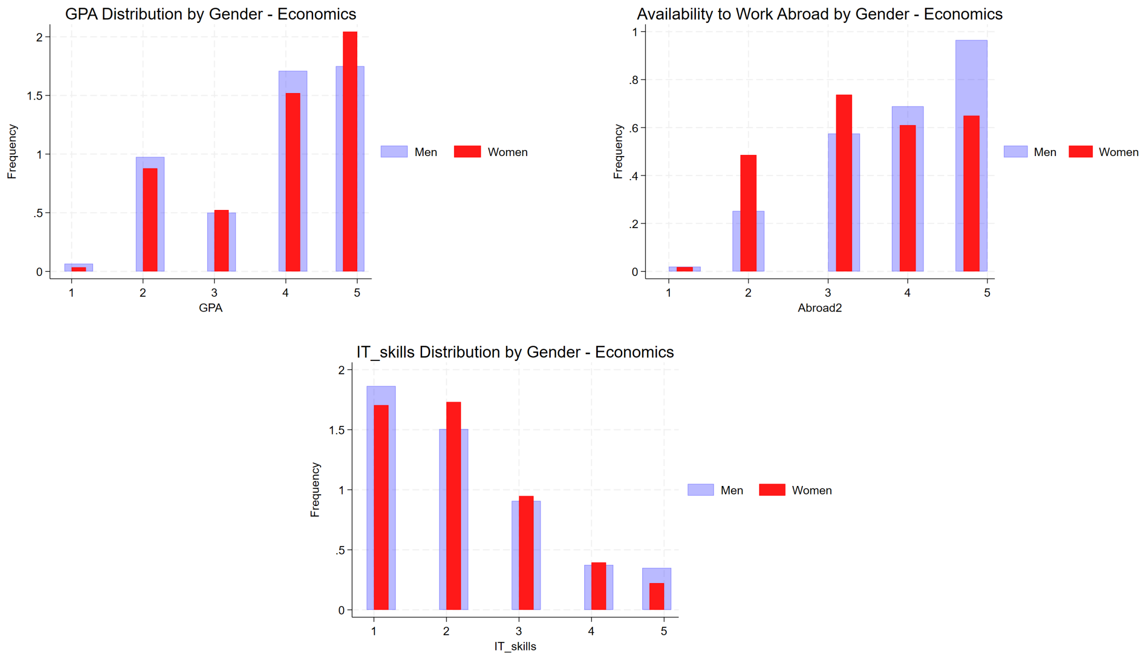

Figure 1: Comparison of GPA, Availability to Work Abroad and IT skills by Gender — Economics and Management

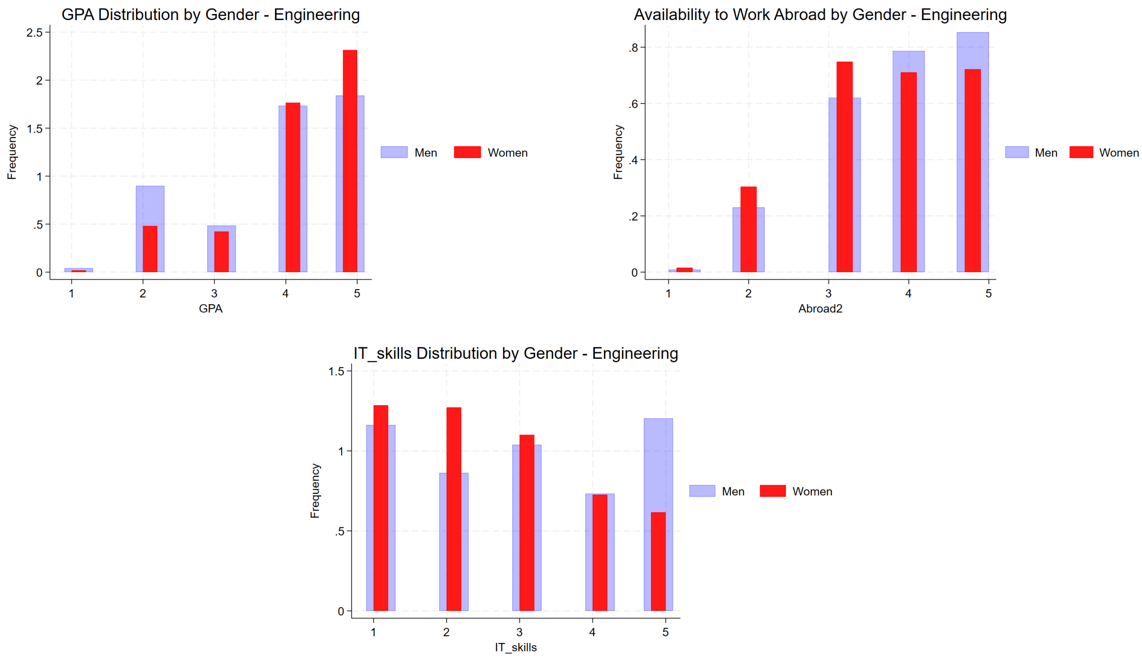

Figure 2: Comparison of GPA, Availability to Work Abroad and IT skills by Gender — Engineering

The contrast between strong academic achievement and weaker mobility intentions is further illustrated in Table 2, which reports correlations between GPA and willingness to work abroad, and between GPA and IT skills. Associations are statistically significant only for Economics and Management (for both men and women), and their magnitudes are small—the largest in absolute value is about 0.057 for GPA and willingness to work abroad among women in Economics and Management -while in Engineering there is no significant association with GPA. For IT skills, the last two columns show no significant association with GPA in any field. The results in Table 2 indicate that academic performance is largely orthogonal to both mobility intentions and IT skills.

Table 3 reports the correlation between the two components of productivity we consider. We find modest positive correlations between mobility intentions and IT skills (roughly 0.09–0.11 across groups), suggesting that they capture related dimensions of productivity while remaining distinct from GPA. These patterns support our modeling approach, in which employers form expectations using private (CV) signals alongside public, group-level information on gender, field of study, and other components of productivity.

	GPA & Abroad		GPA & IT Skills	
Field of study and gender	Corr coeff.	p-value	Corr. coeff.	p-value
Economics and Man. (Men)	0.0396	0.0627*	0.0298	0.1682
Economics and Man. (Women)	0.0565	0.0135**	0.0012	0.9578
Engineering (Men)	-0.0137	0.4029	0.0067	0.6876
Engineering (Women)	0.0541	0.0682*	-0.0443	0.1399

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

Field of study and gender	Correlation coefficient	p-value
Economics and Man. (Men)	0.0899	0.0000***
Economics and Man. (Women)	0.1139	0.0000***
Engineering (Men)	0.0915	0.0000***
Engineering (Women)	0.1119	0.0002***

Table 3: Correlation between Availability to Work Abroad and IT skills by Gender and Field of Study

Mobility intentions and IT skills systematically differ across genders. Mobility intentions may affect productivity through channels such as spatial flexibility, availability for geographically dispersed opportunities, and readiness to accept demanding assignments. Similarly, IT skills capture technological proficiency and adaptability, which are increasingly rewarded in modern labor markets. The evidence that men report higher willingness to work abroad and stronger IT skills than women provides two plausible channels through which wage gaps can emerge at the very start of professional trajectories.

The literature provides supporting evidence on the importance of these additional components such as mobility intentions and IT skills in shaping labor market outcomes. Prior work shows that gender differences in commuting and geographic mobility contribute to job sorting and wage disparities. In particular, Le Barbanchon et al. (2021) estimate that women's higher aversion to long commutes explains about 10% of the gender wage gap in France. Similarly, Black and Spitz-Oener (2007) link technological change to shifts in women's job tasks and productivity, underscoring the importance of tech-related competencies. Cortés et al. (2020) argue that technological advances can affect the gender wage gap by altering the returns to specific skills, while Hargittai (2002) documents early evidence of a gender digital divide beyond mere internet access. More recently, Bustelo (2019) and Zhang (2024) show that inequalities in digital proficiency translate into wage disparities, with women receiving lower returns to IT skills even when employed in similar occupations. Taken together, these findings highlight that both spatial flexibility and technological skills can meaningfully contribute to early earnings differences, aligning with our focus on mobility intentions and IT skills as complementary components of productivity.

Table 4: Motivating Facts: Wages, GPA, Mobility Intentions, and IT skills by Gender and Field of Study

	Economics and Management		Engineering	
	Men	Women	Men	Women
Availability to work abroad	3.93	3.55	3.89	3.72
It skills (quintiles)	2.16	2.13	2.99	2.62
	t-tests Men vs Women			
t-statistic (Available to work abroad)	10.94		4.99	
p-value	0.000***		0.000***	
t-statistic (IT skills)	0.78		7.45	
p-value	0.434		0.000***	

Notes: The table reports average monthly wages (euros), GPA on a 30-point scale, average responses to the willingness-to-work-abroad question (higher values indicate greater availability), and average IT skills (measured in quintiles of the constructed index), by gender and field of study. In addition to wages and GPA, systematic gender differences are also observed in mobility intentions and IT skills: men are consistently more willing to work abroad and report higher technological proficiency, while women maintain higher academic performance across the two fields. Source: AlmaLaurea survey data, Bologna University graduates, 2015–2022.

To complement these averages, Figures A.1–A.3 in Appendix A plot trends in average wages by gender and graduation cohort for the fields of interest. A persistent and sizable gender wage gap is visible one year after graduation, and it remains relatively stable over time.

These insights motivate our extension of Phelps (1972), in which productivity depends not only on human capital but also on other components such as job mobility-related preferences and IT skills. By modeling these additional determinants, we capture how gender differences in both geographic flexibility and IT proficiency may influence employers' beliefs and salary choices. A detailed description of the dataset and all variables is provided in Section 4.1.

3 The model

We propose a simple statistical discrimination model that highlights gender differences. Unlike standard models of statistical discrimination, which focus exclusively on human capital, our model incorporates an additional productivity component—such as mobility intentions or IT skills—that employers may interpret as a proxy for candidates' motivation, perseverance, and flexibility (see literature cited in the introduction).

Consider an economy in which a large number of graduates enter the labor market. Employers make a salary offer to each graduate that aligns with their expected productivity.[6] We assume that productivity is given by

$$\pi = \theta + h + a, \tag{5}$$

where θ represents innate ability, h is human capital and a represents a graduate's additional component of productivity.

However, 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 information about the graduate's acquired human capital, h, and the other component of productivity, a. Additionally, employers may use gender and field of study as a *public signal* of productivity, since—as shown by the existing empirical literature and confirmed by our descriptive statistics—the distribution of human capital and the other productivity-related trait systematically varies across gender and field of study in the candidate population.

Graduates

There are two populations of graduates, one of males and one of females. Gender is denoted as $g \in \{m, f\}$.

Each graduate of both populations is endowed with innate ability θ, normally distributed according to $\theta \sim \mathcal{N}\left(0, \sigma_\theta^2\right)$. In what follows, it is convenient to use the precision of the distribution $\rho_\theta = \frac{1}{\sigma_\theta^2}$. Innate ability determines an individual's production potential before the acquisition of human capital, net of the additional productivity component.

Each graduate is associated with a field of study, denoted by t ("topic"). During their university studies, graduates acquire human capital h, a one-dimensional measure of academic achievement and acquired skills. Human capital is distributed according to gender g and field of study t:

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

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

The third component of productivity, a, is unrelated to the level of human capital; see Table 2. Its distribution depends on gender g but not on the field of study t:

$$a_g \sim \mathcal{N}\left(\bar{a}_g, \frac{1}{\rho_{a_g}}\right), \tag{7}$$

In what follows, we make the following assumption.

Assumption 1 *Suppose* $\bar{h}_{ft} > \bar{h}_{mt}$ *and* $\bar{a}_f < \bar{a}_m$.

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 ($\bar{h}_{ft} > \bar{h}_{mt}$), 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.

Recall that we interpret the additional component a either as willingness to relocate for work or as IT skills. The second inequality of Assumption 1, ($\bar{a}_f < \bar{a}_m$), can be checked in our descriptive statistics of Table 4. Specifically, male graduates, on average, report both a greater willingness to relocate for work and higher IT skills. The former finding on willingness to work abroad is consistent with Le Barbanchon et al. (2021) and Liu and Su (2024), while the latter is in line with evidence on 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 dispersion of these distributions. While information on mean differences is publicly available and likely observable by employers, it is less plausible that employers have accurate knowledge of the precision of these distributions. Hence, $\rho_{h_{ft}} \gtrless \rho_{h_{mt}}$ and $\rho_{a_f} \gtrless \rho_{a_m}$.

Signals

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 the information contained in the CV), while the other two are public signals, generally available to all employers.

- 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 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:

$$c_i = \theta_i + h_i + a_i + \varepsilon_i. \tag{8}$$

where ε_i is a normally distributed error term with mean 0 and precision ρ_c, capturing the noise in the CV as a signal of productivity. The additive specification in equation (8) entails independence between human capital and the additional component of productivity. Evidence from Table 2 indicates that this condition appears to be satisfied.

As long as human capital and the additional component of productivity are distributed differently by gender, the latter can be considered a signal of productivity. The same applies to the field of study as long as human capital is distributed differently according to t. Since this is the case, g and t are common signals in that employers acquire information based on the distribution of human capital and the other component of productivity within a given group (gender and field of study).

Labor market

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

$$w_{igt} = E\left(\pi_i | c_i, g, t\right). \tag{9}$$

Expected productivity depends on the information contained in the CV (the private signal), as well as on the distribution of human capital across gender and field of study and on the distribution of the additional productivity component by gender in the overall population (which together constitute the public signals). From Bayes rule (DeGroot, 2005), equation (9) can be expanded to determine the relevance of each signal:

$$w_{igt}(c_i) = \frac{\rho_{h_{gt}}}{\rho_{h_{gt}} + \rho_{a_g} + \rho_c}\overline{h}_{gt} + \frac{\rho_{a_g}}{\rho_{h_{gt}} + \rho_{a_g} + \rho_c}\overline{a}_g + \frac{\rho_c}{\rho_{h_{gt}} + \rho_{a_g} + \rho_c}c_i. \tag{10}$$

In general, the entry salary offered to candidate i of gender g and field of study t depends on the precision and average of both human capital and the additional productivity component, as well as on idiosyncratic features contained in the CV, summarized by the precision of the random error term ρ_c. In particular, the first two terms on the right-hand side of equation (10) capture the share of expected productivity inferred from the public signals, i.e., from the distributions of human capital and the additional productivity component among graduates of gender g in field t. The third term of the right-hand side of equation (10), instead, represents the share of expected salary explained by the idiosyncratic information in the CV (i.e., the private signal).

Equation (10) highlights the role of signals precision in determining expected salary. When the distributions of human capital and the additional productivity component are highly precise (high $\rho_{h_{gt}}$ and/or ρ_{a_g}), the marginal contribution of the CV to explaining an individual's productivity becomes relatively small. The opposite applies if the CV is a highly accurate measure of productivity (high ρ_c). Employers evaluating a graduate with an unexpectedly good CV, given her or his group gt, will attribute the positive result to high productivity.

To understand the relevance of gender as a common signal, it is useful to study the relationship between individual performance indicated in the CV, c_i, and a candidate's salary, $w_{igt}(c_i)$, and see how it differs by g. This allows us to test the model's predictions regarding the gender wage gap. Equation (10) shows that this relationship is linear, with intercept

$$I_{gt} = \frac{\rho_{h_{gt}}}{\rho_{h_{gt}} + \rho_{a_g} + \rho_c}\overline{h}_{gt} + \frac{\rho_{a_g}}{\rho_{h_{gt}} + \rho_{a_g} + \rho_c}\overline{a}_g > 0, \tag{11}$$

and slope

$$S_{gt} = \frac{\rho_c}{\rho_{h_{gt}} + \rho_{a_g} + \rho_c} > 0. \tag{12}$$

Given that the distributions of human capital and the additional productivity component vary by gender and field of study, the linear relationship between c_i and $w_{igt}(c_i)$ may be affected by gender in different ways. Hence, the gender wage gap may go in opposite directions.

3.1 Theoretical results

Comparing the male and female intercepts and slopes in equations (11) and (12) yields, in principle, four possible scenarios for the early gender wage gap. However, as shown in the next section, only two are empirically relevant, depending on whether $\rho_{h_{ft}} \gtrless \rho_{h_{mt}}$ and $\rho_{a_f} \gtrless \rho_{a_m}$ in a given field of study.

Case 1 *The linear relationship between CV and salary is given by* $I_{ft} > I_{mt}$ *and* $S_{ft} < S_{mt}$.

Case 2 *The linear relationship between CV and salary is given by* $I_{ft} < I_{mt}$ *and* $S_{ft} > S_{mt}$.

Figure 3 depicts Case 1. From Assumption 1, $I_{ft} > I_{mt}$ holds if the average human capital is a stronger signal of productivity than the average additional component of productivity, thus pushing the intercept of females higher than that of males. In addition, from (12), $S_{ft} < S_{mt}$ requires:

$$\rho_{h_{ft}} + \rho_{a_f} > \rho_{h_{mt}} + \rho_{a_m}.$$

In general, a higher slope indicates lower precision in the combined gender-related signals. Thus, if the slope is higher for men than for women, the corresponding signals are less precise for men. In other words, the joint distribution of GPA and the average additional productivity component is more dispersed among men. In this case, a strong CV provides relatively more informational value for men than for women, leading to higher expected productivity and, consequently, higher wages for men.

Case 1 is depicted in Figure 3, showing that a gender wage gap in favor of men occurs only when the average CV is sufficiently high, namely, higher than c_t^*. In this case, given the scarce quality of male-related signals, a high-quality CV is expected to be idiosyncratic, that is, related to a high productivity, which in turn ensures a high expected salary.

The opposite applies when Case 2 holds: the intercept of male graduates is higher, indicating that non-academic traits carry more weight as a signal. Conversely, the male

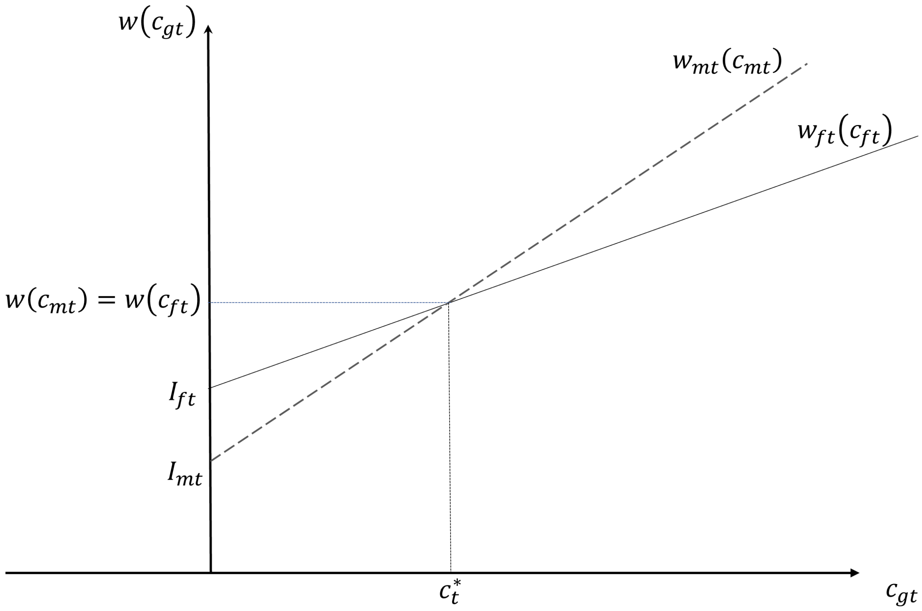

Figure 3: Relationship between the expected salary and the CV for female and male graduates when Case 1 holds.

slope is steeper, suggesting that their gender-related signals are more precise than those of females. Figure 4 shows Case 2: the average c must be sufficiently low—specifically, below c_t^*—for a gender wage gap in favor of men to arise.

Based on this discussion, we may state the following.

Proposition 1 *Suppose there is a level of CV c_t^* such that the salary offered to male and female graduates is the same. Then,*

- *if Case 1 holds and $c \geq c_t^*$, the salary for a male graduate is higher than that of a female graduate, and the opposite occurs for $c < c_t^*$;*
- *if Case 2 holds and $c \geq c_t^*$, the salary for a female graduate is higher than that of a male graduate, and the opposite occurs for $c < c_t^*$.*

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 these productivity-related components—*mobility intentions* (a proxy for motivation and flexibility) and *IT skills* (a proxy for adaptability to evolving work environments and technological change)—improves the explanatory power of the statistical discrimination framework across fields of study.

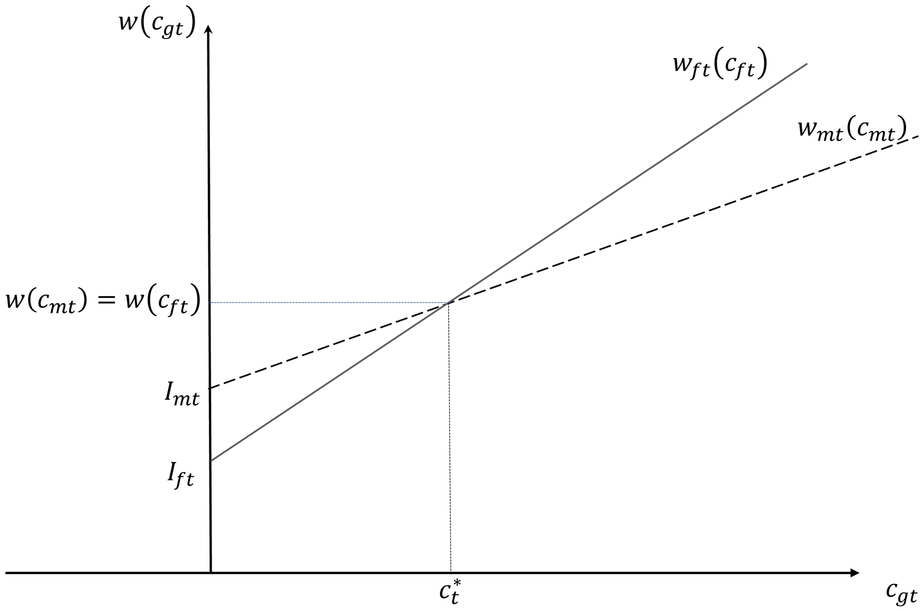

Figure 4: Relationship between the expected salary and the CV for female and male graduates when Case 2 holds.

4.1 Data and Descriptive Statistics

We use microdata from the AlmaLaurea Graduate Survey on Italian five-year graduates from the University of Bologna in Economics and Management and Engineering. Our sample covers the 2015–2022 cohorts observed one year after graduation.[7] We restrict the sample to Italian citizens, younger than 35 at graduation, and employed full-time (≥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).

We concentrate on two fields of study that differ markedly in gender composition and career trajectories. According to AlmaLaurea, women represent about 46% of graduates in Economics and Statistics and 23% in Engineering. These differences matter because the gender balance within a field can shape both preferences and outcomes through channels such as: (i) stereotypes and self-selection into majors, (ii) pre-existing differences in student interests, and (iii) peer effects once students are embedded in the academic environment. However, analyzing the two fields of study jointly is meaningful, since in both cases job candidates face career prospects not only in Italy but also abroad, along with a relatively high probability of employment one year after graduation.

Our main variables include standard measures of human capital as well as two other

[7] 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. To capture the early gender wage gap in its most immediate form, we restrict attention to the one-year follow-up.

components of components of productivity. 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 proficiency in operating systems, programming languages, word processors, spreadsheets, databases, computer-aided design, internet navigation and online communication, website creation and management, data networks and protocols, multimedia production and editing, and presentation software. 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 area equal to one if the respondent reports *good* or *excellent* proficiency. The unweighted sum across the eleven areas 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.

Table 5: **Summary Statistics for graduates in Economics and Management**

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

Notes: This table presents summary statistics for graduates from the University of Bologna between 2015 and 2022 in fields related to *Economics and Management* who reported being employed one year after graduation. The sample is further restricted to individuals working more than 35 hours per week, graduating before the age of 35, and not foreign-born. Monthly wages are expressed in euros, GPA is measured on a 30-point scale, and diploma grades on a 100-point scale. IT skills is coded from 1 to 5, while fluency in a foreign language is a binary indicator.

Table 6: **Summary Statistics for graduates in Engineering**

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

Notes: This table presents summary statistics for graduates from the University of Bologna between 2015 and 2022 in fields related to *Engineering* who reported being employed one year after graduation. The sample is further restricted to individuals working more than 35 hours per week, graduating before the age of 35, and not foreign-born. Monthly wages are expressed in euros, GPA is measured on a 30-point scale, and diploma grades on a 100-point scale. IT skills is coded from 1 to 5, while fluency in a foreign language is a binary indicator.

Table A.1 in Appendix A reports descriptive statistics for the full Bologna graduate sample. Here we focus on the three fields of interest. Tables 5 and 6 provide summary statistics for *Economics and Management* and *Engineering*. A clear pattern emerges: Engineering graduates earn higher wages and include a lower share of women, whereas Economics and Management graduates display a more balanced gender composition but 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 comparable. When considering mobility intentions we find that they are quite similar while IT skills are substantially stronger among Engineering graduates. Taken together, these facts suggest that early wage differences across fields are not primarily driven by academic achievement, but are instead consistent with a role for gender composition, mobility intentions, and IT skills as components of productivity.

4.2 Calibration

In this section, we calibrate the parameters of the theoretical model to assess its predictive validity. The first step is to compute the average CV, $\overline{c}_{gt}$, for each gender g and field of study t, as predicted by the model:

$$\overline{c}_{gt} = \overline{h}_{gt} + \overline{a}_g, \tag{13}$$

where $\overline{h}_{gt}$ denotes average human capital and $\overline{a}_g$ average of the additional traits of productivity, which can refer to mobility intentions or IT skills.

The second step is to use equations (11) and (12) to recover the intercept and slope parameters of equation (10), which identify the threshold c_t^*: the CV level at which expected salaries for men and women are equal within a field. Comparing $\bar{c}_{gt}$ to c_t^* reveals whether average CVs fall in the region where the model predicts a wage gap in favor of men—namely, when $\bar{c}_{gt}$ lies above c_t^* in Case 1 (Figure 1) or below c_t^* in Case 2 (Figure 2).

To isolate the specific role of the two additional components (mobility intentions and IT skills) of productivity in explaining gender wage gaps, we contrast two specifications for each of them in turn. In the baseline model, productivity is inferred only from the group identity and a noisy signal of human capital (proxied by GPA), following the classic framework *à la* Phelps (1972); this corresponds to a model where the terms a and a_i do not appear in equations (5) and (8), respectively. In the augmented specifications, we add the additional component of productivity a, first proxied by mobility intentions (willingness to work abroad) and then by IT skills. Comparing each augmented version with the baseline allows us to test whether accounting for these additional traits enhances predictive accuracy and better explains the observed gender asymmetries in early labor market outcomes. In all cases, the inverse of the R^2 is used as a proxy for the unobserved idiosyncratic information contained in the graduates' CV.

The two panels of Table 7 summarize the model parameters 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, calculated as the inverse of the variance. Notice that, in the "GPA" row of the table, the ρ_g column indicates $\rho_{h_{gt}}$, in the "Abroad" row it indicates ρ_{a_g}, and in the "IT skills" row it indicates ρ_{j_g}.

In the last column, we report the value of $1 - R^2$ from models estimated using only High GPA, and from models including both GPA and willingness to work abroad and from models inclugind GPA and IT skills.[8] This value serves as a proxy for the parameter ρ_c, capturing residual uncertainty in the productivity signal after accounting for observed characteristics.

[8]The parameters are obtained from OLS regressions with monthly wage as dependent variable and GPA, gender, diploma grade, 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. The R^2 is obtained from these regressions, with $1 - R^2$ serving as a proxy of the unexplained variance.

Panel a): Economics and 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)	2.1678	1.4546	0.6875	2.1394	1.2266	0.8152	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	0.909
Abroad (1–5)	3.8981	0.9805	1.0199	3.7274	1.0571	0.9460	0.904
IT skills (quintile)	2.9906	2.2123	0.4520	2.6232	1.7804	0.5617	0.905

Table 7: Estimated model inputs by gender and field of study: mean, variance, and signal precision (ρ_g) for GPA (quintile), willingness to work abroad (Abroad), and IT skills (quintile).

Note: These parameters are used to simulate predictions under the baseline (GPA only) and the augmented versions of the statistical discrimination model (GPA+Abroad, GPA+IT skills). The last column reports $1-R^2$, used as a proxy for ρ_c.

Across both fields, female graduates have higher GPA than male graduates, consistent with greater academic attainment among women. By contrast, men report systematically higher willingness to work abroad and higher IT skills. These contrasts are modest in Economics and Management and more pronounced in Engineering. Overall, the distributional differences in mobility intentions and IT skills point to these additional components of productivity that may contribute to early wage differences beyond academic achievement, which are central to the mechanisms emphasized in Assumption 1 of the theoretical model.

Looking at the variances, we also find gender differences. For GPA, women exhibit slightly lower variance than men in both fields, implying a more concentrated distribution around higher academic performance ($\rho_{h_f} > \rho_{h_m}$), especially in Engineering. By contrast, the variance in willingness to work abroad is generally higher among women ($\rho_{a_f} < \rho_{a_m}$), with the gap particularly pronounced in Economics and Management, indicating greater heterogeneity in mobility preferences within the female group. A different pattern emerges for IT skills: women display lower variance than men in both fields ($\rho_{s_f} > \rho_{s_m}$), especially in Engineering, 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 mean levels of other traits 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.

Panel a) Economics and Management

Model's controls	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
Intercept	1.7456	1.8278	2.5199	2.3945	1.8704	1.9300
Slope	0.5500	0.5371	0.3507	0.3593	0.3855	0.3621

Panel b) Engineering

Model's controls	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
Intercept	1.8108	2.2455	2.2036	2.4461	2.0680	2.3389
Slope	0.5341	0.4622	0.4190	0.3750	0.4191	0.3567

Table 8: Estimated Parameters by gender and field of study.

Using the information in Table 7, we are able to calibrate the average cv in equation (13). These are summarised in Table 9, in the first row of each panel. In Table 9, $t \in \{1, 2\}$, and 1 and 2 correspond to Economics and Management and Engineering, respectively. Columns 2 and 3 show the average cv by gender when only human capital is considered. It corresponds to the statistical discrimination framework *a là* (Phelps, 1972) relying solely on human capital.

Columns 4 and 5 show the average cv that emerges from our model, when mobility intentions are considered together with human capital. Here we provide an example to clarify our procedure. By Table 7 we know that a male graduate of Economics has GPA 3.8204 and, in Phelps (1972), this is what explains productivity, so that the average CV is given by it (see the first slot in Table 9). Instead, since in our model productivity is also explained by mobility intentions, given in Table 7 by 3.5925, the average CV is represented by equation (13) and it is given by $3.8204 + 3.5925 = 7.41239$. Finally, columns 6 and 7 show the average CV that emerges from our model when IT skills are considered alongside human capital. The same procedure is adopted as for mobility intentions.

Panel a) Economics and Management

	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
$\bar{c}_{g1}$	3.8204	3.9318	7.7514	7.4869	5.9882	6.0712
c_1^*	10.275		14.581		2.547	

Panel b) Engineering

	GPA		GPA + Abroad		GPA + IT skills	
	Males	Females	Males	Females	Males	Females
$\bar{c}_{g2}$	3.8868	4.1752	7.7849	7.9026	6.8774	6.7984
c_2^*	6.0459		5.5114		4.3413	

Table 9: Average CV $\bar{c}_{gt}$ and thresholds c_t^* for Economics and Management and Engineering.

The next step is to calibrate the thresholds c_t^* from Proposition 1. Table 8 shows the estimated parameters of intercepts and slopes from equations (11) and (12) for each field of study, separately for men and women. As in the previous table, three specifications are considered: the baseline model, which includes only GPA as a proxy for human capital (columns 2 and 3); the model augmented with mobility intentions, which also incorporates willingness to work abroad as a component of productivity (columns 4 and 5) and the model augmented with IT skills, where digital competencies are added as an additional productivity component (columns 6 and 7). From the information in Table 8, we derive the thresholds c_t^* for every field of study, using the intercept and slope in equation (11) and equation (12), respectively. The thresholds are reported in Table 9, in the second row of each panel. We evaluate each field of study separately.

Let us start with Economics and Management. Consider columns 2 and 3 of Table 8, which correspond to the baseline statistical discrimination framework *à la* Phelps (1972), relying solely on human capital. In this case, female graduates have a higher intercept (1.8278 vs. 1.7456) and a slightly lower slope (0.5371 vs. 0.550) than male graduates. This configuration is consistent with Case 1 in the theoretical model. By Proposition 1, a gender wage gap favoring men should emerge if male and female average CVs, $\bar{c}m1$ and $\bar{c}f1$, both lie above the threshold c_1^*. However, as reported in Table 9, both average CVs lie below c_1^*. 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.

Turning to columns 4 and 5, which add mobility intentions as a component of productivity, women now display a lower intercept (2.3945 vs. 2.5199) and a slightly higher slope (0.3593 vs. 0.3507) than men. This configuration corresponds to the case described in Case 2. By Proposition 1, a gender wage gap in favor of men should emerge if the average CVs of men and women lie below the threshold c_1^*. As reported in Table 9, both average CVs indeed lie below this threshold. Hence, the model augmented with mobility intentions is consistent with the empirical evidence and explains the emergence of a gender wage gap in favor of men.

When IT skills is introduced (columns 6 and 7), the pattern is qualitatively similar to that with mobility intentions: men display a lower intercept (1.8704 vs. 1.9300) and a higher slope (0.3855 vs. 0.3621) than women. As shown in Table 9, male average CVs increase relative to females once IT skills are incorporated, and the threshold condition predicts a wage gap in favor of men. Thus, in Economics and 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 lie above c_t^* for a gender wage gap in favor of men to emerge. As shown in Table 9, and similarly to Economics, excluding mobility intentions would predict a wage gap in favor of female graduates. It is the inclusion of mobility intentions or IT skills that accounts for the observed gender wage gap in favor of male graduates.

These calibration findings are therefore consistent with the theoretical results and support the inclusion of factors other than human capital in explaining the emergence of a gender wage gap in favor of men at the early stages of a graduate's career.

4.3 Empirical Results

In this subsection, we investigate the determinants of early wage variation across graduates in the two fields of focus. We estimate a simple OLS model where the dependent variable is the monthly wage one year after graduation:

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

where $Female_i$ is a dummy equal to one for women, and $Abroad_i$ captures the respondent's reported willingness to work abroad.

We also estimate the following model:

$$Wage_i \;=\; \alpha_0 \;+\; \alpha_1\,Female_i \;+\; \alpha_2\,\mathrm{ITskills}_i \;+\; \Gamma_i \;+\; \Lambda_i \;+\; \epsilon_i, \tag{15}$$

where $\mathrm{ITSkills}_i$ captures the respondent's information-technology proficiency.

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 this framework, the coefficient α_1 measures the gender wage gap after conditioning on individual and environmental characteristics. Extending the specification with either

$Abroad_i$ or $ITskills_i$ allows us to test whether systematic gender differences in mobility intentions and IT skills help explain part of the observed gap.

Table 10: Regression Results by Field of Study: *Abroad*

	Economics and Management		Engineering	
VARIABLES	(1) monthly wage	(2) monthly wage	(3) monthly wage	(4) monthly wage
Female	-79.483***	-69.044***	-106.292***	-102.616***
	(14.123)	(14.294)	(12.773)	(12.715)
Abroad		33.650***	-	34.821***
		(6.671)		(5.345)
Observations	3,702	3,702	4,556	4,556
R-squared	0.092	0.098	0.091	0.100
Env. Controls	YES	YES	YES	YES
Ind. Controls	NO	YES	NO	YES

Notes: Robust standard errors in parentheses. OLS regressions with monthly wage as the dependent variable, gender and availability to work abroad as explanatory variables, plus individual and environmental controls. Data: AlmaLaurea (graduates University of Bologna, 2015–2022). *** p<0.01, ** p<0.05, * p<0.1.

As shown in Table 10, the gender wage gap is sizeable and statistically significant across both fields of study. The gap is smallest in Economics and Management, where women earn on average about 80 euros less per month than men, and largest in Engineering, with a monthly gap of about 105 euros. These figures confirm that gender disparities in earnings emerge very early in professional careers, despite comparable educational attainment.

Introducing the variable *Abroad*, which measures the respondent's willingness to work abroad, slightly reduces the magnitude of the gender wage gap in Economics and Management (from €79 to €69) and Engineering (from €106 to €102). This suggests that part of the differential can be traced to systematic gender differences in mobility intentions, consistent with the descriptive evidence presented earlier.

Turning to the coefficient on *Abroad*, we find it to be positive and highly significant in both Economics and Management (where the gap decreases by €34) and Engineering (where the gap decreases by €35), indicating that graduates open to international mobility command substantially higher wages. This supports the interpretation of willingness to relocate as a productivity-related trait—capturing flexibility, ambition, or access to a wider set of job opportunities—that is valued and rewarded by employers.

Table 11 reports the regression results when *It skills* are included as an additional explanatory variable.

Table 11: Regression Results by Field of Study: *IT skills*

	Economics and Management		Engineering	
VARIABLES	(1) monthly wage	(2) monthly wage	(3) monthly wage	(4) monthly wage
Female	-80.038***	-79.755***	-107.737***	-99.110***
	(14.105)	(14.096)	(12.735)	(12.815)
IT skills	-	5.954		19.973***
		(6.325)		(3.781)
Observations	3,702	3,702	4,556	4,556
R-squared	0.091	0.092	0.089	0.095
Env. Controls	YES	YES	YES	YES
Ind. Controls	NO	YES	YES	YES

Notes: Robust standard errors in parentheses. OLS regressions with monthly wage as the dependent variable, gender and IT skills as explanatory variables, plus individual and environmental controls. Data: AlmaLaurea (University of Bologna graduates, 2015–2022). *** p<0.01, ** p<0.05, * p<0.1.

As shown in Table 11, the gender wage gap remains sizeable and statistically significant both fields of study. The gap is again smallest in Economics and Management, where women earn about €80 less, while in Engineering, the penalty is around €107. These results confirm that early wage disparities between men and women are robust to the inclusion of IT skills in the specification.

Turning to the coefficient on *IT skills*, we find some field heterogeneity. In Economics and Management, the coefficient is positive but does not achieve statistical significance, suggesting that IT skills are not systematically rewarded or penalized in this field at the early career stage. By contrast, in Engineering, IT skills are associated with a significant wage increase of about €20 per month. These results indicate that, unlike mobility intentions, IT skills are not uniformly valued across the two fields.

Our findings so far suggest that the impact of these additional components of productivity on early wages varies across fields. Mobility intentions matter most in Economics and Management and Engineering, where IT skills significantly improves earnings prospects and helps account for part of the gender wage gap but only in Engineering, while do not display significant effects in Economics and Management.

5 Concluding remarks

Building on a statistical discrimination framework à la Phelps (1972), we extend the model to include, in addition to human capital, another determinant of productivity: either mobility intentions or IT skills. This richer formulation allows the framework to reproduce the early gender wage gaps in favor of men observed in the data. In our dataset, and more generally in Italy, as in most developed countries, women consistently outperform men in academic achievement across fields, which on its own would not predict a female wage penalty. Once productivity is modeled as a function of mobility intentions or IT skills—two dimensions in which men tend to score higher on average—the model's predictions align with the evidence: mobility intentions account for the gaps observed in Economics and Management and

Engineering, while IT skills better account for the patterns in Engineering.

A key intuition from our analysis is that employers form expectations not only from candidates' individual CVs (private signals) but also from group-level distributions (public signals), such as gender and field of study. Since mobility intentions and IT skills are systematically related to gender, they become relevant through this channel: when combined with human capital, they shape employers' beliefs about expected productivity and thus influence wage-setting decisions.

Our findings indicate that the salience of these additional productivity components is field-specific. *Mobility intentions* are relevant in both Economics and Management and Engineering, where they help explain early gender wage gaps, while *IT skills* play a stronger role in Engineering, further narrowing the residual gap.

Our results suggest that early gender wage differentials arise not only from academic achievement but also from how employers interpret and weight other components of productivity. Future work could consider alternative traits—such as willingness to work irregular hours, openness to specific job tasks, or preferences for certain work environments—that may matter more 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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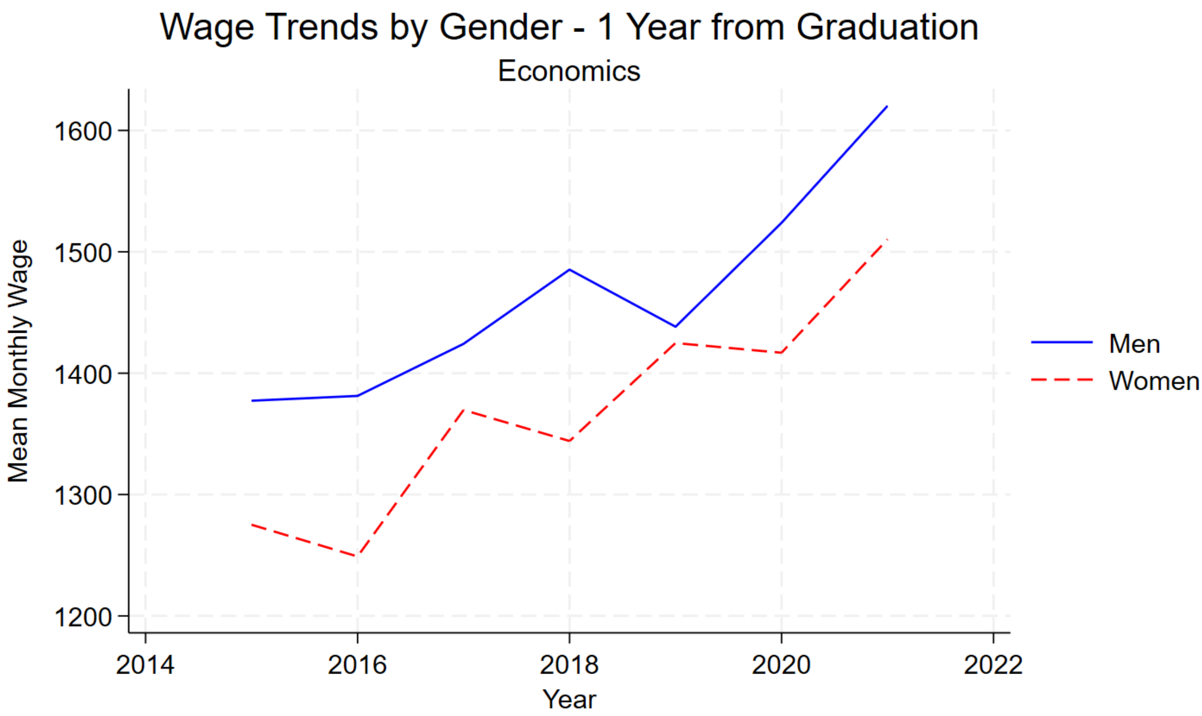
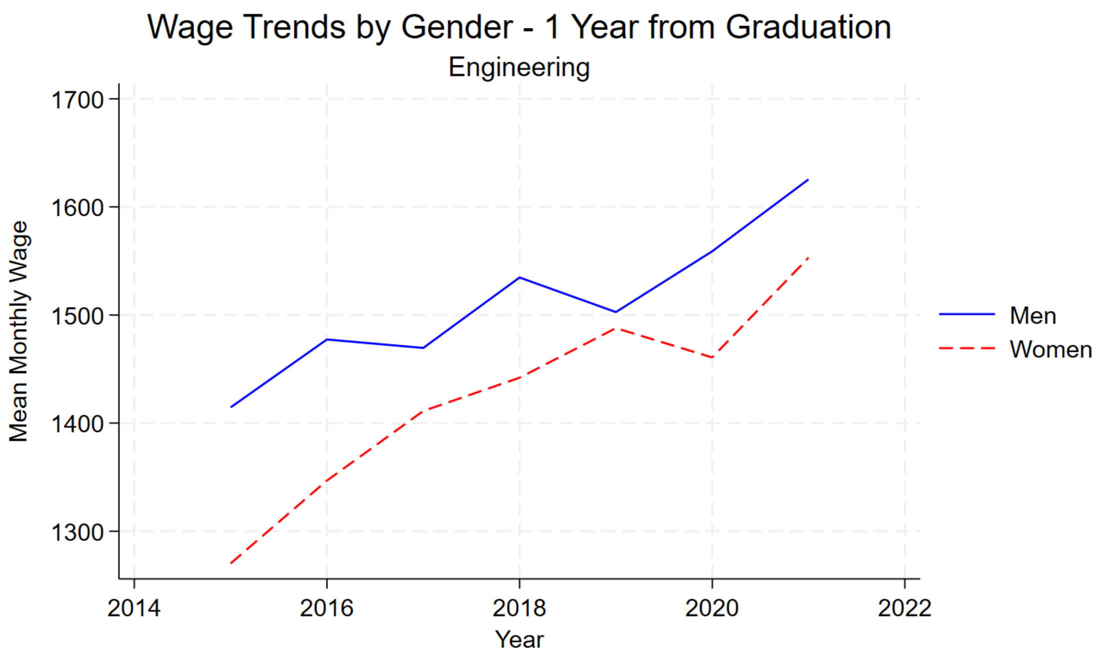
A Additional Tables

Figure A.1: Wage and Gender – Economics and Management



Note: Trends in wages by graduation year and gender for graduates in *Economics and 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.2: 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.

Table A.1 reports summary statistics for the full sample of five-year laureates from the University of Bologna between 2015 and 2022.

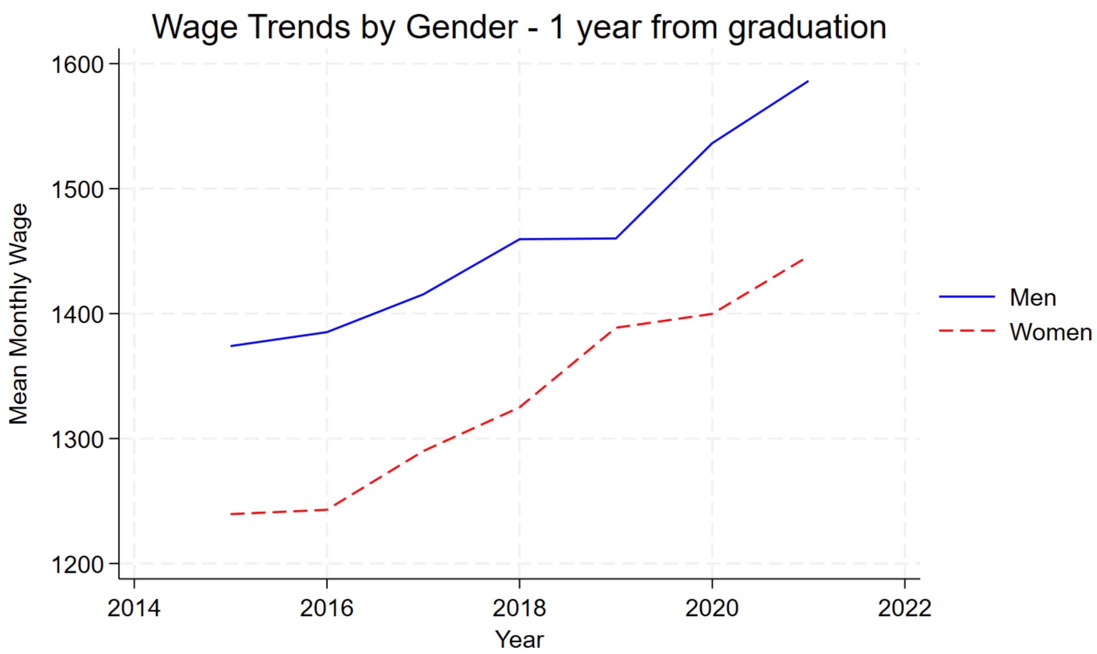
Table A.1: Summary Statistics for the Full Sample of Graduates

	Mean	Std. Dev.	Min	Max	Obs.
Monthly wage (€)	1396.50	447.66	200.00	4250.00	23137
Female	0.51	0.50	0.00	1.00	24060
Availability to work abroad	0.55	0.50	0.00	1.00	24060
GPA (18–30 scale)	26.88	2.10	18.60	30.00	24058
Diploma grade (60–100 scale)	81.93	11.70	60.00	100.00	23720
Weekly hours worked	42.17	4.63	37.00	63.00	24060
Foreign language	0.13	0.34	0.00	1.00	24060
IT skills	2.87	1.47	1.00	5.00	24060
Observations	24060				

Notes: This table presents summary statistics for graduates from the University of Bologna in all fields of study between 2015 and 2022 who reported being employed one year after graduation. The sample is restricted to individuals working more than 35 hours per week, graduating before the age of 35, and not foreign-born. Monthly wages are expressed in euros, GPA is measured on a 30-point scale, and diploma grades on a 100-point scale. Monthly wages are reported in euros. GPA is measured on a 30-point scale, and diploma grades on a 100-point scale. IT skills range from 1 to 5, while Availability to work abroad and knowledge of a foreign language are coded as a binary variable.

In Figure A.3, we present wage trends by graduation year and gender for the full sample of graduates from the University of Bologna between 2015 and 2022.

Figure A.3: Wage and Gender in the full sample of graduates



Note: Trends in wages by graduation year and gender in all fields of study. Data come from all 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.

Alma Mater Studiorum - Università di Bologna
DEPARTMENT OF ECONOMICS

Strada Maggiore 45
40125 Bologna - Italy
Tel. +39 051 2092604
Fax +39 051 2092664
http://www.dse.unibo.it