The College Melting Pot: Peers, Culture and Women's Job Search*

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Abstract

Gender norms are widely recognized as key drivers of persistent gender gaps in the labor market, yet little is known about how these norms evolve or can be influenced. This paper provides new evidence that exposure to university classmates born in more gender-equal environments shapes women's early-career labor market outcomes. I exploit quasi-random, cross-cohort variation in the geographical origins of peers within Master's programs in Italy, leveraging comprehensive administrative and survey data covering the universe of students. Exposure to female classmates born in provinces with one standard deviation higher female labor force participation significantly increases women's likelihood of entering full-time jobs and sorting into higher-paying occupations, reducing early-career gender gaps by 20–40%. Using new data I collected on students' job-search preferences and beliefs, I show that peer effects operate primarily through two channels: reductions in the value women place on hours' flexibility, and learning about job offer arrival rates. Peer effects are highly asymmetric, concentrated among women from less gender-equal regions, indicating that exposure can mitigate early-career disadvantages rooted in childhood environments. The results underscore the potential of educational policies that promote geographical diversity to shift gender norms and advance gender equality in the labor market.

JEL classification: J16, J22, I24, R23, Z13. **Keywords**: gender gaps, childhood environment, labor supply, role models, aspirations.

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1 Introduction

Cultural norms are pervasive and shape the payoffs to many individual decisions. One critical domain where their influence is particularly pronounced is in the economic behavior of men and women. By shaping beliefs and preferences, gender norms are widely recognized as key determinants of the persistent gender gaps in the labor market—above and beyond traditional factors such as human capital, comparative advantage, or discrimination (Bertrand, 2020, Cortes and Pan, 2023). Even as the economic costs of conforming to traditional gender roles have risen, their persistence continues to hinder gender convergence in the labor market (Fernandez, 2013, Fortin, 2015, Kleven, Forthcoming).

Understanding the determinants of cultural change is therefore a significant yet insufficiently understood problem. While some studies examine cultural change as an intergenerational learning process (Fogli and Veldkamp, 2011, Fernandez, 2013), most of the literature documents the persistence of norms rather than uncovering the drivers of change (Giuliano, 2020). In particular, we have limited evidence on whether, and how, the social environment or public policy can influence gender norms, reflecting the scarcity of empirical settings and data that allow for credible identification.

This paper provides new evidence that exposure to college classmates from more gender-equal areas significantly shapes women's labor market behavior. Exploiting quasi-random, cross-cohort variation in the geographic origins of students within Master's programs, together with comprehensive administrative and survey data covering the near-universe of Italian students, I show that peer exposure significantly reduces the large gender gap in full-time employment that emerges at graduation. A key innovation of the paper is to ask *why* being exposed to peers born in more egalitarian places affects women's (and not men's) labor market decisions. Drawing on detailed data on students' job-search preferences and beliefs, I find that these peer effects are driven by (i) changes in women's job-search preferences and (ii) social learning, rather than improved academic outcomes or beneficial labor market connections.

Italy offers a compelling setting to study cultural norms. First, it exhibits exceptionally wide geographic variation in gender equality, with female-to-male labor force participation rates ranging from 44% to 86% across provinces, mirroring the scale of cross-country differences.[1] Due to substantial internal mobility (affecting about 60% of students), Italian universities bring together students from provinces with varying levels of gender equality, who systematically differ in their beliefs about gender roles and their labor market expectations. Moreover, the small size of Master's programs (with a median of 35 students)

[1] These disparities in labor force participation align closely with strong differences in gender attitudes, firms' gender preferences in hiring, and differential full-time employment rates between female and male university graduates.

and the two-year duration of graduate studies create an environment of close social interactions and repeated exchanges of information about labor market opportunities and aspirations.

Women raised in more or less gender-equal provinces systematically differ in their beliefs regarding gender roles and their expectations about labor market opportunities, which translate into divergent early-career outcomes. This relationship is estimated using a refined *epidemiological approach*, focusing on graduates who work in a different province from where they were born (about half of the sample).[2] The core idea is that, conditional on studying in the same Master's program and working in the same local labor market, individuals share similar human capital and job opportunities but differ in their early-life exposure to female role models and gender norms. The results show that women (but not men) from provinces with higher female labor force participation are more likely to enter full-time employment post-graduation. These patterns are robust to controls for academic performance and other observables, and cannot be explained by differential selection into migration.

This paper asks: *Does being surrounded by peers from more (or less) gender-equal backgrounds in college shape women's labor market behavior?* Identifying such peer effects is challenging, since students self-select into programs, so that peer groups are not randomly assigned. To overcome selection issues, I exploit a key feature of the setting: because Master's programs are small, they exhibit substantial cohort-by-cohort variation in the geographic origins of enrolled students, which generates quasi-random exposure to peers from different cultural backgrounds. I leverage this variation to estimate the causal effect of peer exposure to gender norms—measured primarily by female labor force participation (FLFP) in students' home provinces, along with alternative gender-related indicators.[3] This analysis is made possible by access to rich longitudinal data that track changes in peer composition over time across 1,572 Master's programs, a key advantage over existing datasets on university graduates, which are typically limited to smaller samples from selective institutions. For this design to yield causal estimates, changes in peer composition must be orthogonal to time-varying unobserved determinants of students' labor market outcomes. Leveraging high-quality information on a broad set of predetermined individual characteristics—including students' educational histories, academic performance, and family background— I probe the validity of this approach through an extensive set of standard and novel randomization checks.[4]

[2]This approach is similar to recent studies by Kleven, Forthcoming, Charles et al., 2024 and Boelmann et al., 2025.

[3]This strategy builds on the research design introduced by C. M. Hoxby, 2000, and widely used to estimate the impact of students' characteristics on educational outcomes.

[4]These include balancing tests, placebo estimates, and simulation-based evidence showing that the identifying variation resembles random shocks. I also exclude programs with potential non-random

I document three main findings. First, exposure to female classmates from provinces with higher female labor force participation significantly increases women's likelihood of entering full-time employment after graduation. This effect operates in part through greater sorting into occupations where full-time work is more prevalent. The magnitude is economically meaningful: a one standard deviation increase in peers' provincial FLFP (8.5 percentage points) raises women's probability of full-time employment by 2 percentage points, increases weekly hours worked by 3.3%, and translates into a 3.7% gain in net monthly earnings. In contrast, men's outcomes remain unaffected, implying that peer exposure narrows early-career gender gaps by 21 to 40%, depending on the outcome. Importantly, these effects are not driven by broader provincial characteristics: they remain robust across a range of gender-specific indicators and fade or disappear when using non-gender-related measures, such as per capita income or proxies for overall economic activity.

Second, peer effects exhibit a strong asymmetry across the FLFP distribution: the beneficial impacts of peer exposure are concentrated entirely among women from low-FLFP provinces, while women from more gender-equal backgrounds do not respond to peer composition. Such non-linearities suggest that targeted reassignments of students across peer groups could raise average female earnings overall. Moreover, the setting allows for a direct comparison between horizontal (peer-based) and vertical (origin-based) influences. A one standard deviation increase in the proportion of female classmates from high-FLFP provinces—equivalent to nine additional peers—closes up to 65% of the labor supply gap between women from low- and high-FLFP origins, indicating that peer exposure substantially mitigates early-career disadvantages rooted in childhood environments.

Third, I explore the mechanisms behind these peer effects, a question that remains underexplored due to limited datasets tracking beliefs, preferences, and other difficult-to-observe factors (Sacerdote, 2011; Feld and Zölitz, 2017). Understanding these channels is essential for designing policy interventions that can replicate the benefits of peer exposure without changing group composition (Barrios Fernandez, 2023). Using novel data, I test several potential mechanisms and find evidence for two main channels. First, I find no indication that exposure to high-FLFP peers improves women's academic performance, increases migration to stronger labor markets, or leads to referrals to better jobs. This suggests that peer effects are not driven by better credentials or expanded opportunities, but by changes in preferences and beliefs. Drawing on data from a mandatory institutional survey at graduation, I analyze students' valuations of job attributes. Women exposed to peers from high-FLFP provinces place less value on non-pecuniary attributes—particularly flexibility, leisure time, and the social value of work. These find-

changes in students' composition and flexibly control for program- and region-specific time trends.

ings contribute to a growing literature on gendered job-search preferences,[5] showing that such preferences are shaped by the social environment and remain malleable into early adulthood.

Finally, I field a targeted survey to examine how beliefs and information diffusion drive peer effects. I administered the survey in person to two cohorts of Master's students across several programs at a large university, achieving a 97% response rate among attending students. The first key finding is that women from low-FLFP provinces enter university with more pessimistic beliefs about full-time employment and view ambition as less socially acceptable. Holding job-search effort and job type constant, they anticipate receiving 13% fewer full-time job offers than women from high-FLFP areas seeking jobs in the same region.[6] These expectations are strong predictors of job outcomes and account for about one-fifth of the observed full-time employment gap between students from low- and high-FLFP origins. These results underscore the role of information frictions, alongside preferences and attitudes, in perpetuating norms around female labor market participation. I also document convergence in labor market beliefs during the course of graduate study. Between the first and second year, the initial gap in expectations about full-time job offers narrows by over 70%, driven entirely by upward revisions among women from more traditional backgrounds. This asymmetric belief updating closely mirrors the non-linear peer effects discussed earlier and offers compelling evidence that social learning plays a role in shaping labor market expectations. In contrast, gaps in perceived gender roles remain largely stable over time, echoing past evidence that such views are more resistant to change (Giavazzi et al., 2019).

Related literature. This article contributes to three strands of research. First, a large body of work, following the seminal contribution of Fernandez, 2007, has documented the persistent role of cultural norms in shaping women's economic decisions, particularly around the time of motherhood (e.g., Antecol, 2000, Fernandez and Fogli, 2009, Blau et al., 2011, Fortin, 2015, Bertrand et al., 2015, Cortes et al., 2023, Ichino et al., 2024, Kleven, Forthcoming, Boelmann et al., 2025). I complement this work by showing that early exposure to gender norms influences women's labor supply choices already at labor market entry—well before family formation—potentially compounding later-life effects. More importantly, while the mechanisms behind cultural persistence remain poorly understood, I identify a novel channel: survey evidence reveals that women from more

[5]See Mas and Pallais, 2017, Wiswall and Zafar, 2018, Wiswall and Zafar, 2021, Le Barbanchon et al., 2021, Fluchtmann et al., 2024, Caldwell and Oren, 2024.

[6]These beliefs also correlate with perceived employer discrimination. By contrast, I find no regional differences in fertility expectations or intended labor supply post-motherhood, possibly consistent with recent evidence that individuals often misperceive motherhood-related career costs (Kuziemko et al., 2018).

traditional backgrounds systematically underestimate their chances of receiving full-time offers. These expectations shape job search behavior and early-career outcomes, reinforcing inequality through an anticipatory mechanism. This channel has direct policy relevance: relatively low-cost interventions, such as improving access to accurate labor market information, could meaningfully reduce gender gaps, especially among women from traditional backgrounds. These results complement recent work by Bursztyn et al., 2020 and Cortes et al., 2023, who emphasize information frictions, such as misperceptions about second-order beliefs, in the persistence of gender norms.

Second, this paper contributes to the small but growing literature on the transmission of gender norms—an area where empirical evidence remains limited (Giuliano, 2020). Most existing work emphasizes intergenerational channels, particularly maternal influence: for example, Olivetti et al., 2020, Mertz et al., 2024, and Kleven et al., 2024 show that women's labor market and occupational choices are shaped by the employment behavior of their classmates' mothers during childhood and adolescence. More closely related, an emerging set of studies examines horizontal transmission through peers, such as coworkers (Boelmann et al., 2025) and neighbors (Maurin and Moschion, 2009, Jessen et al., 2024). My contribution is twofold. First, I provide the first large-scale evidence on how exposure to culturally diverse college classmates affects gendered labor market outcomes. Leveraging variation in peer composition across cohorts within Master's programs, I show that women from more traditional backgrounds significantly increase full-time employment rates when exposed to peers from more gender-egalitarian regions—partially offsetting the disadvantages of their childhood environments. Second, I go beyond documenting peer effects and provide direct evidence that they operate through shifts in preferences and beliefs, rather than improved opportunities, complementing previous work that emphasizes the role of peers in providing labor market connections (Kramarz and Skans, 2014, Zimmerman, 2019, Fischer et al., 2023, Hampole et al., Forthcoming, Campa, 2025, Einiö, 2025).

Third, this study contributes to the growing literature on job seekers' misperceptions about the labor market. While standard search models assume rational expectations, a large body of evidence documents systematic belief distortions (see Mueller and Spinnewijn, 2023 for a review). Across diverse settings, individuals tend to overestimate their job-finding probabilities (Spinnewijn, 2015, Caliendo et al., 2015, Conlon et al., 2018, Arni, 2019, Potter, 2021, Mueller et al., 2021, Bandiera et al., 2023, Banerjee and Sequeira, 2023), and misperceptions have also been identified regarding expected wages and outside options (Drahs et al., 2018, Cortes et al., 2023, Alfonsi et al., 2024, Jäger et al., 2024). This paper contributes along three dimensions. First, I study beliefs about the arrival rates of part-time versus full-time job offers—a dimension previously overlooked.

My elicitation method holds job-search effort constant, isolating beliefs about labor demand. Second, I document substantial heterogeneity by early-life environment: women from low-FLFP regions hold more pessimistic expectations, which persist despite migration and explain part of their higher likelihood of working part-time. Third, I provide new evidence on belief updating: over the course of the Master's program, women from more traditional provinces substantially revise their expectations. This convergence is consistent with social learning and highlights the role of peer exposure in reducing information frictions.

The paper proceeds as follows. Section 2 introduces the institutional setting and data. Section 3 describes the "melting pot" at Italian universities. Section 4 documents early-career gender earnings gaps and estimates cultural persistence. Section 5 outlines the identification strategy and assesses its validity. Section 6 presents the main peer-effect estimates, and Section 7 tests their robustness across specifications and samples. Section 8 examines non-linearities, and Section 9 investigates underlying mechanisms. Section 10 uses new survey data on beliefs to deepen the analysis of cultural persistence and social learning. Section 11 concludes with implications for education policy.

2 Institutional Background and Data

2.1 Admission and Functioning of Graduate Education

Admission to Master's Programs. Since the early 2000s, higher education in Italy has followed a two-cycle structure consisting of a three-year bachelor's degree (*laurea triennale*) followed by a two-year master's degree (*laurea magistrale*). The two cycles are formally distinct, but progression is the norm: approximately 70% of bachelor's graduates enroll in a master's program.

Admission to master's programs is conditional on satisfying curricular prerequisites, primarily a minimum number of credits in specified subject areas. Students may therefore change fields between undergraduate and graduate studies, provided they meet these eligibility requirements. In addition to curricular criteria, many programs are selective.[7] Admissions decisions commonly rely on entry examinations, undergraduate grade point averages, and, in some cases, interviews. Applicants are typically ranked based on these criteria, and admission is competitive. Additional requirements—such as English language certifications, motivation letters, or reference letters—vary across institutions and programs. Only a limited number of fields, including medicine, health sciences, architecture, psychology and primary education, are subject to a centralized national entrance

[7]For example, admission to a master's program in economics typically requires prior coursework in economics, statistics, or related social sciences totaling at least 53 credits out of the 180 credits required for the bachelor's degree.

examination.

Throughout the paper, I use *degree* to refer to a master's program at a given university, *course* to denote an individual subject within a degree, and *field of study* for a broad disciplinary category offered across multiple institutions.

Tuition Fees. Approximately 90% of Italian students are enrolled in public universities. Tuition fees vary across institutions and degree programs and are generally income-contingent. Regional governments set income thresholds for need-based grants, which usually cover tuition, housing and meal vouchers. In the sample used in this paper, 23% of students receive such financial aid; among the remainder, the average annual tuition fee is €1,262.

2.2 Data Sources and Sample

The empirical analysis combines administrative records and survey data at a scale and level of detail that, to my knowledge, are unique in the literature on college graduates. The core data come from university registries affiliated with the AlmaLaurea consortium and cover approximately 93% of students enrolled in Italian universities, including nearly all public universities and a subset of private institutions.[8] These records are linked to two surveys administered by AlmaLaurea: a pre-graduation survey and standardized post-graduation follow-up surveys. Together, these sources provide information on students' educational histories, family backgrounds, job-search preferences, and labor market outcomes. I complement them with an original survey designed to elicit students' beliefs about labor market opportunities and gender roles.

Administrative student-level data. The administrative records contain rich individual-level information across three dimensions. First, they include detailed measures of academic performance during the Master's program — number of exams taken, GPA and final degree grade — as well as prior educational histories, including high school type, grades and bachelor's degree characteristics. Second, they provide demographic information: age, immigration status and municipality of both birth and residence. Third, and most importantly for identification, they contain unique program identifiers and precise enrollment and graduation dates, which allow me to reconstruct cohort composition within each Master's program over time. I use these data to identify peer groups and to construct measures of students' geographical background based on their province of residence prior to enrollment. Crucially, the population-wide coverage means I observe the complete set of peers within every program and cohort — a level of granularity that

[8] A list of participating universities is available at https://www.almalaurea.it/chi-siamo/gli-atenei.

is, to my knowledge, unavailable in any existing dataset on university graduates.

Institutional pre-graduation survey. As part of the graduation process, students at all participating universities are required to complete a pre-graduation survey administered by their institution after passing all required exams. The compulsory nature of this requirement yields a response rate close to 100%.[9] The survey collects three categories of information particularly relevant for this study: students' job-search intentions and valuations of different job attributes, which I use to investigate preference-based mechanisms; socio-economic background, including parents' occupations and education levels; and detailed educational histories — high school and bachelor's degree characteristics, prior academic performance and work activities undertaken during studies.

Follow-up surveys. The AlmaLaurea consortium conducts standardized follow-up surveys one, three, and five years after graduation. Because the enrollment cohorts in my sample are recent, the analysis relies on the one-year follow-up survey. Students are contacted initially by email and subsequently by phone, yielding response rates of 73.7% for women and 73.2% for men at the one-year horizon — high by the standards of graduate surveys and, importantly, balanced across gender.[10] The survey collects the primary labor market outcomes used in the analysis: net monthly earnings, usual weekly hours, contract type (part-time versus full-time, open-ended, fixed-term, seasonal, or no contract), occupation, industry, and job location. It also provides retrospective measures of job-search intensity and timing. Earnings and hours are reported in bins, which I convert to continuous measures using bin midpoints.[11]

Survey on students' beliefs. Administrative records reveal whether peers affect labor market outcomes but provide limited evidence on the mechanisms through which these effects arise. I therefore designed an original survey, informed by qualitative interviews with female students at several universities, to elicit beliefs and expectations relevant to women's labor supply decisions. The questionnaire measures expectations about job-offer arrival rates and labor market prospects, perceived employer discrimination, attitudes toward gender roles, fertility expectations, and anticipated labor supply following motherhood. It also collects information on students' social networks, including romantic partnerships within the program, and their perceptions of peer influence. Crucially, the

[9] Although students may formally decline or withhold consent for data use, over 90% of graduates both complete the questionnaire and authorize its use for research.

[10] Response rates decline to 70.4% and 70.3% after three years, and to 64.2% and 64.3% after five years.

[11] For example, reported net earnings are categorized as $<$ €250, €250–€500, €500–€750, €750–€1000, ..., $>$ €3000. I assign €187.50 to the lowest category and €3750 to the top-coded category. Weekly hours are categorized in five-hour intervals from "$<$ 5 hours" to "$>$ 60 hours."

survey tracks these beliefs over time: it was administered in person in Fall 2023 to two cohorts of Master's students — first-year and second-year — across a sample of programs at a large university, enabling me to observe how beliefs evolve during graduate study. In-person administration and lottery incentives generated a response rate of 97% among students attending class on the survey date. Full details on survey design and elicitation procedures are provided in Section 10.

2.3 Sample description

The sample consists of students who enrolled in Master's programs between 2012 and 2016.[12] I restrict the sample to degree programs that (i) enroll at least one male and one female student in each cohort and (ii) satisfy this condition for at least two consecutive years, as required to estimate gender-specific peer effects. These restrictions exclude 3.5% and 6.1% of students, respectively.

The baseline sample further excludes international students, defined as those who resided outside Italy before enrollment. These students account for 2.07% of the initial sample.[13] This restriction is primarily due to data limitations: for international students, the administrative records do not provide geographical information at a level comparable to an Italian province and therefore do not permit assignment of the province-level gender-equality measures used in the analysis. The exclusion is unlikely to materially affect the analysis because international students constitute a small share of the overall sample and are concentrated in fewer than 25% of Master's programs.

Accordingly, I construct all peer-background measures using only classmates who resided in Italy before enrollment. International students nevertheless remain part of the broader cohort environment, as changes in their prevalence could be correlated with changes in the geographical composition of Italian students. All baseline specifications therefore control for the share of international students in each program and cohort. As a robustness check, I retain international students in the estimation sample; the resulting estimates are virtually unchanged.

The final sample comprises 316,470 students enrolled in 1,572 degree programs across 71 universities: 182,792 women and 133,678 men. It includes only students who remain enrolled for the full duration of their Master's program.[14]

[12] Since the available data are organized by graduation cohort, I reconstruct enrollment cohorts using students' enrollment and graduation dates recorded in university registries.

[13] Approximately 40% of international students previously resided in Asia, with China and India accounting for the largest shares. Another 36% previously resided in Europe, primarily in France and Germany, followed by Albania, Russia, and Spain.

[14] A limitation of this approach is that it excludes dropouts, who represent approximately 6% of students enrolled during the 2012-2016 period (ANVUR, 2023).

Background characteristics and academic records. Table I reports descriptive statistics on students' background characteristics and academic performance, separately by gender. The variables are drawn from administrative records and the institutional survey, with the latter available for approximately 91% of students.

Women outperform men academically along several dimensions. During their Master's studies, they earn higher GPAs and final grades. They also exhibit stronger prior academic performance, including higher high school and bachelor's degree grades. Women are more likely to have attended an academic-track high school (*liceo*)—84.2%, compared with 71.4% of men—and their academic outcomes are less dispersed. The largest differences in field of study arise in engineering and the humanities: 27% of men study engineering, compared with 8.2% of women, whereas 24.7% of women and 10.4% of men study the humanities. Similar proportions of women and men enroll in science, chemistry, or biology programs, at approximately 13%.

Turning to family background, approximately 20% of female students have a mother or father with tertiary education, and about one-third have fathers employed in high-SES occupations. Male students come from comparatively more advantaged backgrounds, as reflected in higher levels of parental education and a larger share of fathers employed in high-SES occupations. Maternal labor force participation is 71% among female students and 73% among male students, substantially above the corresponding national averages.

Labor market outcomes and the job-search process. Table II presents summary statistics on labor market outcomes from the one-year follow-up survey. At the time of the survey, approximately 12% of both female and male graduates are pursuing further education, while most have entered the labor force: 66.6% of women and 71.3% of men are employed in a standard employment relationship or participating in an internship. Unemployment is slightly higher among women: 16% are actively searching for work, compared with 12.1% of men. In addition, 5.2% of women and 4.0% of men are out of the labor force. These differences largely reflect gender differences in field-of-study composition.

Among employed graduates, women experience less favorable labor market outcomes than men. Average monthly earnings are €1,077.8 for women and €1,324 for men. Despite almost all women (93.6%) expressing a preference for full-time employment in the pre-graduation survey,[15] 30.7% of employed women work part-time, compared with 13.8% of employed men. Women are also underrepresented in high-earning occupations and

[15]Preference for full-time work is based on responses to the questions "Are you available to accept a full-time position?" and "Are you available to accept a part-time position?" Responses range from "Not at all" to "Absolutely yes." Students who are weakly more inclined to accept a full-time than a part-time position are classified as preferring full-time work.

industries, more likely to work in the public sector, less likely to hold permanent contracts, and more than twice as likely as men to work without a formal contract.

Turning to job-search behavior, over 80% of both women and men are in their first post-graduation job. Women report having held slightly more jobs, consistent with shorter contract durations and more frequent transitions. Most graduates begin searching within one month of graduation, but women accept their first offer slightly later — three months after graduation on average, compared to 2.7 months for men.[16] Despite accepting offers later, women report lower job satisfaction: rates of on-the-job search are substantially higher, particularly among part-time employed women — 58% of whom are actively seeking another position, compared to 30.8% of full-time employed women. Women are also more likely to experience skill mismatch, as reflected in lower rates of using skills acquired during their Master's degree.

3 The College Melting Pot

Three features of the Italian university system make it particularly well suited for studying how exposure to peers from different geographical backgrounds shapes labor market behavior. First, universities bring together students from provinces that differ markedly in female labor force participation and other indicators of gender equality. Second, high rates of interprovincial mobility generate substantial diversity in students' geographical backgrounds within Master's programs. Third, these programs are relatively small and follow a largely common curriculum, creating sustained opportunities for interaction among classmates over two years of graduate study.

3.1 Geographical Variation in Female Labor Force Participation

Italy exhibits pronounced geographical variation in female labor force participation and gender attitudes, as documented in previous work (Campa et al., 2011; Carlana, 2019; Carrer and Masi, 2024). Across provinces, the ratio of female to male labor force participation (FLFP/MLFP) ranges from 43% to 86%—a degree of variation comparable to that observed across countries. These differences are closely associated with regional variation in attitudes toward gender roles. For example, the share of respondents who disagree with the statements *Being a housewife is just as fulfilling as working for pay"* and *Men should be given priority when jobs are scarce"* ranges from 16% to 67% across Italian regions (EVS, 1990-2008).

I characterize the gender environment in students' provinces of origin using six indicators: (*i*) FLFP and (*ii*) the FLFP/MLFP ratio, measured for different age groups

[16] This variable measures months after graduation at which job search begins, with "0" indicating search beginning before or immediately after graduating.

at the province level; (*iii*) the share of private-sector firms reporting no preference for male workers, measured at the province level; (*iv*) the share of female college graduates employed full-time at labor market entry and (*v*) the corresponding female-to-male ratio, both measured at the regional level; and (*vi*) the female-to-male literacy ratio recorded in the 1911 Italian Census.

Most indicators are measured at the province level, corresponding to the NUTS-3 classification. Italy comprises 103 provinces, administrative units situated between municipalities and regions.[17] I assign students to provinces using their place of residence before university enrollment, as recorded in the administrative registries. Pre-enrollment residence coincides with province of birth for approximately 80% of students. Throughout the paper, I refer to this location as the student's province of origin.

Because these measures aim to capture the local labor market environment to which students were exposed during their formative years, they are constructed using data prior to university enrollment. The first two indicators - province-level FLFP and FLFP/MLFP ratios - are computed as averages over 2004-2007. The measure of firms' hiring preferences draws on the *Indagine Excelsior* (Unioncamere), a nationally representative survey of approximately 100,000 Italian firms conducted in 2003, covering about one-third of firms in manufacturing and services.[18] The labor market outcomes of earlier female graduate cohorts are constructed focusing on *stayers* — graduates employed in their region of origin — to isolate local labor market conditions from selection into migration. Due to sample size constraints in smaller provinces, these indicators are aggregated at the regional level (NUTS-2). Finally, the historical literacy measure draws on the 1911 Italian Census and serves as a long-run proxy for deeply rooted gender norms, largely predating the modern labor market conditions captured by the other indicators.

Summary statistics of gender equality indicators. Table III documents substantial cross-province variation across all measures. FLFP ranges from 27% to 67%; among women aged 25–34, it ranges from 38% to 86%. This variation is not simply a reflection of differences in overall labor market activity. Male labor force participation varies over a range less than half as wide, while the FLFP/MLFP ratio ranges from 43% to 86% in the working-age population and from 47% to 95% among individuals aged 25–34.[19] Variation is also substantial along other dimensions: the female-to-male ratio of college graduates employed full-time ranges from 55% to 83%, and the share of firms reporting

[17] In 2010, the average province had approximately 551,000 residents. Provincial populations ranged from more than four million in Rome to fewer than 60,000 in Ogliastra, Sardinia.

[18] Since 1997, the Excelsior Survey, run in partnership with the Ministry of Labor, ANPAL and the EU, has collected annual information on firms' hiring intentions, including preferences for male or female candidates, or gender-neutral preferences.

[19] Figure I maps the geographic distribution of these measures across Italian provinces.

no preference for male hires from 35% to 71%. Table A.I shows no systematic differences in the geographical origins of female and male graduates.

Provinces also differ along broader social and economic dimensions, summarized in Table A.II. Several characteristics — including MLFP, per-capita income, and childcare availability — are moderately to strongly correlated with FLFP (Table A.III). Section 7 directly addresses whether the estimated peer effects reflect these broader provincial characteristics rather than gender-specific factors, finding that they do not.

3.2 Student Mobility and Peer Diversity

A second key feature of the Italian context is the high rate of student mobility across provinces. During the period covered by this analysis, more than 57% of students enrolled in a university outside their province of residence, and 31% moved to a different region entirely.

Several institutional factors explain this pattern. As of 2016, Italy had 89 public universities — serving over 90% of the student population — located in only 52 of the country's 103 provinces. Many institutions are specialized, limiting the availability of certain fields locally.[20] Roughly 20% of Italians aged 18–19 reside in provinces without any higher education institution, and only 77% have access to both STEM and non-STEM programs within their home province (Braccioli et al., 2023). Students face no restrictions on applying to universities outside their region. Together, these features - combined with regional disparities in post-graduation labor market opportunities - generate the high level of inter-provincial mobility observed in the data.

Mobility patterns in the sample. Among students in the sample, 58.9% of women and 55.4% of men move outside their birth province to pursue graduate studies (Table IV). Students of both sexes tend to relocate to areas with more egalitarian gender environments relative to their provinces of origin. Movers are present across virtually all degree programs: fewer than 1% of programs have no movers, and in 50% of programs more than half of students are movers (Figure II, Panel A). Mobility remains high at the job-search stage: 51.6% of men and 44.1% of women work outside their province of origin one year after graduation, while the majority - 68.4% of women and 65.3% of men - find their first job in the same region where they studied (Table V).

Table VI examines women's mobility patterns by quartile of FLFP in their province of origin. Substantial out-migration is observed across all quartiles, but women from low-FLFP provinces migrate over longer distances and more often leave their home region entirely. Destination patterns differ markedly by origin: women from high-FLFP provinces

[20] For instance, degrees in information technology were offered at only 29 universities, and agriculture and veterinary sciences at just 24.

tend to relocate to similarly egalitarian areas, so that 67% of their peers originate from above-median FLFP provinces, compared to only 27% for women from low-FLFP areas. Differences in field of study across groups are modest. Return migration patterns also diverge: 68.8% of women from low-FLFP provinces work outside their province of origin after graduation, compared to 45.9% of women from high-FLFP areas. The corresponding analysis for male students reveals similar patterns, indicating that these mobility gradients are not specific to women (Table A.IV).

Peers' diversity within Master's programs. High rates of student mobility generate substantial heterogeneity in the geographical composition of Master's programs. Panel (B) of Figure II illustrates this "melting pot" by documenting the representation of students from low- and high-FLFP provinces within each program. While more than one-third of programs are composed exclusively of students from below-median FLFP regions, the majority display a balanced mix across quartiles, and only 5% consist entirely of students from above-median FLFP areas.[21] Table A.V provides additional evidence on within-program diversity. In the 2016 enrollment cohort, the average program contains 48 students drawn from approximately 14 provinces, and 21% of students are the sole representative of their province of origin within the program. Pre-existing educational ties are even less prevalent: more than 72% of students have no classmate from their high school, and the average student has only 0.5 same-high-school peers. Master's programs therefore expose students to classmates from a broad range of geographical backgrounds, most of whom they are unlikely to know through prior schooling.

3.3 Size and Relevance of Peer Groups

I define a student's peer group as the set of classmates entering the same Master's program in the same year. This definition is considerably more granular than those commonly used in the peer-effects literature, which often encompass an entire school or university cohort. The median program cohort contains 35 students, with cohort size ranging from 4 to 410 students (Figure III, Panel A). Gender composition is generally balanced, with relatively few programs heavily dominated by either women or men (Panel B).

The structure of these programs offers two advantages for the analysis. First, their relatively small size and largely common curriculum create repeated opportunities for interaction, making the program cohort a plausible approximation to students' relevant academic peer environment. Students remain in the program for two years and complete a largely common set of courses under the curricular framework established by Ministerial Decree 270/2004. Elective courses account for only approximately 10% of the credits

[21] Figure A.I provides a more detailed view of the distribution of geographical origins across programs.

required for graduation. Students are therefore repeatedly exposed to many of the same classmates throughout the program.

Second, small cohorts generate meaningful year-to-year fluctuations in peer composition. These fluctuations provide the within-program variation in peers' geographical backgrounds used in the identification strategy. In larger programs, the law of large numbers would attenuate such cohort-to-cohort variation.

Quantity and quality of social interactions. Evidence from the original survey described in Section 10 confirms that interactions among classmates are frequent. More than 70% of students spend leisure time with classmates at least once a week (Figure IV). These interactions exhibit limited geographical homophily: only 10% of students report socializing primarily with classmates from their own province, while 32% socialize primarily with classmates from other provinces and 58% report a balance between the two groups. More importantly for the outcomes studied in this paper, interactions among classmates extend beyond socializing to discussions of career plans and labor market opportunities. Female classmates appear to be particularly salient sources of such information for women: 80% of female students discuss their career aspirations with female classmates, compared with 63% who do so with male classmates. These exchanges are also frequent, with 46% reporting that they discuss career aspirations with female classmates often or very often.

4 Motivating Facts

This section documents two empirical patterns that motivate the analysis. First, a substantial gender earnings gap emerges at labor market entry, driven primarily by differences in hours worked rather than hourly wages. Second, among women who move away from their province of birth, early-career labor supply varies systematically with female labor force participation in the province of origin, even conditional on degree program, cohort, and labor market at destination. Together, these patterns establish a strong association between early-life environments and women's labor supply at the beginning of their careers.

4.1 The Early-Career Gender Earnings Gap

Despite achieving stronger academic outcomes—as reflected in higher GPAs and stronger prior academic records—a substantial gender earnings gap emerges at labor market entry. Among employed graduates, women earn 11% less per month than observationally similar male peers from the same Master's program (Table VII), corresponding to an average annual net difference of approximately €1,780. This early-career earnings gap is driven primarily by differences in hours worked rather than by hourly wages. Women are 5

percentage points less likely to hold full-time positions and report working 8.3% fewer hours per week than comparable male peers.[22] As a result, approximately one-third of the unconditional gender gap in full-time employment documented in Table II arises within programs, among students graduating from the same Master's cohort. These differences persist after controlling for occupation and industry fixed effects and are not explained by geographic mobility patterns (Table A.VII). In contrast, the residual gender gap in hourly wages is comparatively small, at 2.9%.[23]

These differences are pervasive across programs and fields of study. Figure V plots degree-specific fixed effects for women against the corresponding fixed effects for men. Outcomes for women and men are strongly positively correlated across degree programs, but women earn less (Panel A) and work fewer hours (Panel B) throughout the distribution. Nor do these gaps appear to be confined to the initial transition into employment. Using administrative data for the same population, Bovini et al., 2026 show that gender differences persist, and in some cases widen, during the first five years after labor market entry.

Two commonly cited explanations for early-career gender gaps—realized fertility and early acceptance of job offers—appear unlikely to account for the patterns observed in this setting.

Fertility. A large literature attributes a substantial share of gender differences in labor supply to parenthood (Cortes and Pan, 2023). However, several countries—particularly in Southern Europe—exhibit sizable gender inequality in labor market outcomes even prior to childbirth. Italy is a prominent example, with pre-birth inequality accounting for at least 40% of the overall gender gap (Kleven et al., 2025). Consistent with this pattern, realized fertility plays a limited role in explaining early-career gender differentials in the present setting. The average age of women in the sample is 24, with only 3.7% having children and 16.1% being married or cohabiting. Excluding these groups does not materially affect the estimated gender earnings gap (Table A.VIII).

Anticipated fertility could nevertheless affect job choices before motherhood. The original survey provides limited support for this explanation: women expect to have their first child at approximately age 31, well after labor market entry, and only a minority expect to reduce their working hours or leave employment following childbirth. Section 10 examines fertility expectations and anticipated labor supply around motherhood in greater detail.

[22] Conditional on attending the same program, there are no gender differences in employment probabilities (Table A.VI).

[23] Although the estimates in this paper are based on survey data, they are quantitatively similar to those reported by Bovini et al., 2026, who use administrative data linking university records to social security earnings for Italian graduates between 2011 and 2018.

Timing of job acceptances. Gender differences in search behavior may also contribute to early-career earnings gaps. One proposed mechanism is that greater risk aversion leads women to accept job offers earlier in the search process, and that these jobs are of lower quality (Cortes et al., 2023). The descriptive patterns in this setting do not support this particular mechanism. Women and men begin searching at similar times, while women accept their first job offer slightly later than men (Table II). Moreover, the gender earnings gap remains stable across the distribution of time to job acceptance (Figure A.II).

Taken together, these facts document substantial gender differences in hours worked and earnings at labor market entry among highly educated Italian graduates. Although comprehensive evidence on initial labor market outcomes remains scarce in other settings, early-career gender gaps in hours are not unique to Italy. Studies of selected groups of U.S. graduates from elite universities and highly competitive degree programs document similar patterns, although the gaps in those settings tend to emerge some years after labor market entry rather than immediately (Bertrand et al., 2010; Azmat and Ferrer, 2017; Cortes et al., 2023). This difference may reflect both the selectivity of the samples studied and institutional features of the Italian labor market, including its substantially higher incidence of part-time employment.

4.2 Place-of-Origin Exposure to Working Women

I next examine whether women's early-career labor supply is associated with their exposure to working women during childhood. The analysis focuses on movers, defined as female graduates who work in a province other than that of origin. Movers account for approximately half of the sample of working women. By comparing individuals who face the same labor market and institutional conditions at destination but differ in their province of origin, this design isolates variation related to early-life environments, holding contemporaneous labor market conditions constant.

Specifically, I relate women's weekly hours and full-time employment to FLFP in their province of origin, conditional on degree program, cohort, and province of employment. The identifying comparison is therefore between women with similar educational backgrounds who work in the same local labor market but were raised in provinces with different levels of female employment. This exercise is descriptive: province of origin is not randomly assigned, and women who move from different parts of the country may differ along unobserved dimensions.

The estimating equation is

$$Y_{idcp} = a_0 + \phi\, Q4FLFP_{idcp} + \theta_d + \delta_c + \gamma_p + \sum_{k=1}^{K} \lambda_k X^k_{idcp} + \varepsilon_{idcp}, \tag{1}$$

where i denotes a female mover who completed Master's program d in cohort c and is employed in province p. The indicator $Q4FLFP_{idcp}$ equals one if student i was born in a province in the top quartile of the FLFP distribution and zero if she was born in a province in the bottom quartile.[24] The specification includes fixed effects for degree program, cohort, and province of employment. Additional specifications control for GPA and parental background.

Table VIII documents a strong association between women's early-career labor supply and female employment in their province of birth. Female movers originating from high-FLFP provinces work 7.6% more hours per week and are 2.2 percentage points more likely to be employed full-time than those originating from low-FLFP provinces, despite holding the same degrees and working in the same local labor markets. The corresponding difference in monthly earnings is 6.2%, or approximately €880 annually. The estimates are stable after controlling for academic performance and parental background and are robust across all measures of the origin province's gender environment described in Section 3.1.

Movers' selection. A natural concern is that women who move out of high- and low-FLFP provinces differ systematically in ways that also predict labor supply. To assess this possibility, Table IX compares the ability, educational background, and socioeconomic profiles of female movers from provinces in the top and bottom quartiles of FLFP using the same specification as in Equation 1. Overall, movers from high- and low-FLFP provinces appear broadly similar. Parental education levels are comparable, and while some differences emerge in parental occupations, these do not account for the observed association between place-of-origin characteristics and labor supply. If anything, women moving from low-FLFP provinces are positively selected on academic performance: they are significantly more likely to have attended an academic-track high school (*liceo*) and have higher prior grades. To the extent that these characteristics predict stronger subsequent labor market outcomes, this selection would attenuate rather than generate the estimated association.[25]

Male outcomes. To assess whether the results reflect gender-specific exposure rather than general place-of-origin characteristics, I replicate the analysis for male students (Table X). In contrast to the findings for women, men's full-time employment is not systematically associated with FLFP in their province of birth. A modest positive association appears for hours worked, driven by slightly higher rates of overtime, but the magnitude is

[24]For expositional clarity, I restrict this analysis to the two extreme quartiles, where average FLFP is approximately 34% and 62%, respectively. Differences in labor supply are also visible across the intermediate quartiles.

[25]These selection patterns are not specific to women: qualitatively similar patterns emerge among male students (Table A.IX).

substantially smaller than for women and attenuates once additional non–gender-specific geographical controls are included.[26]

Although this analysis is descriptive and does not identify a causal effect of childhood exposure, it documents a robust, gender-specific association between female employment in the province of birth and women's labor supply at career entry. This pattern is consistent with the persistence of gendered labor-market behavior across environments and parallels evidence from the United States and Germany (Charles et al., 2024; Kleven, Forthcoming; Boelmann et al., 2025). It motivates the central question of the paper: whether exposure to university peers from high-FLFP provinces changes women's labor supply and attenuates the influence of their early-life environments.

5 Identification of Peer Effects

The previous section showed that women exposed to higher female labor force participation in their province of origin tend to work more in adulthood—consistent with a mechanism of cultural persistence. But an important follow-up question arises: how do women respond to exposure to peers from different cultural environments? Specifically, does being surrounded by peers from more (or less) gender-equal backgrounds in higher education shape women's labor market behavior?

This section presents the empirical framework designed to answer this question. Identifying peer effects is inherently challenging due to the problem of selection or endogenous peer formation. Since students choose the universities and programs they apply to, peer groups are not randomly assigned. As a result, exposure to particular peer characteristics—such as the average level of gender equality in peers' home provinces—may be correlated with students' own unobserved preferences or motivations, which themselves influence labor market outcomes. This raises the classic issue of correlated effects, as defined in Manski, 1993.

To address the selection issue, my identification strategy exploits within-degree variation in the geographic origins of peers across consecutive enrollment cohorts. This approach, first proposed by C. M. Hoxby, 2000 to study the effects of peers' gender on educational outcomes, has become a standard approach in peer effects research.[27] The core idea is that while students self-select into programs based on time-invariant characteristics - e.g. program quality and average peer composition - they cannot control the precise geographical composition of their entering cohort. This is particularly plausible in

[26] A stronger association emerges when using quartiles of male labor force participation (MLFP).

[27] A non-exhaustive list of related studies includes: Angrist and Lang, 2004, Lavy and Schlosser, 2011, Bifulco et al., 2011, Lavy et al., 2012, Black et al., 2013, S. E. Carrell et al., 2018, Brenøe and Zölitz, 2020, Olivetti et al., 2020, **salvanes**, and Cools et al., 2022.

Italy, where student cohorts exhibit substantial year-to-year variation in regional composition due to large inflows from across the country. The key identifying assumption is that conditional on degree program fixed effects, year-to-year variation in the share of peers from high- versus low-FLFP provinces is as good as random—that is, it is uncorrelated with unobserved determinants of individual labor market outcomes. I provide several tests of this assumption in Subsections 5.2 and 7.1.

Practically, implementing this design requires longitudinal data to track how peer composition within Master's programs evolves over time. My dataset is uniquely suited for this purpose: it covers a large panel of Master's programs—spanning nearly the entire student population in Italy—across multiple enrollment cohorts from 2012 to 2016. This structure enables the analysis of how fluctuations in peer group composition—particularly in exposure to gender-equal norms—shape women's subsequent labor supply behavior.

5.1 The Empirical Model

The associated empirical model is:

$$Y_{idc} = \theta_d + \alpha_c + \gamma FLFP_{idc} + \delta^{FP}\overline{FLFP}^{FP}_{-i,dc} + \delta^{MP}\overline{FLFP}^{MP}_{-i,dc} + \varepsilon_{idc} \tag{2}$$

where i denotes a student enrolled in degree program d and cohort c. $\overline{FLFP}^{FP}_{-i,dc}$ and $\overline{FLFP}^{MP}_{-i,dc}$ represent the leave-one-out average FLFP in the province of origin of same-gender and opposite-gender peers, respectively, within the same degree and cohort. Formally:

$$\overline{FLFP}^{FP}_{-i,dc} = \frac{\sum_{j\neq i} FLFP_{jdc}}{n^{F}_{dc}-1} \text{ if female=1;} \qquad \overline{FLFP}^{MP}_{-i,dc} = \frac{\sum_{j} FLFP_{jdc}}{n^{M}_{dc}} \text{ if female=1;}$$

$$\overline{FLFP}^{FP}_{-i,dc} = \frac{\sum_{j} FLFP_{jdc}}{n^{F}_{dc}} \text{ if female=0;} \qquad \overline{FLFP}^{MP}_{-i,dc} = \frac{\sum_{j\neq i} FLFP_{jdc}}{n^{M}_{dc}-1} \text{ if female=0;}$$

Because the leave-one-out approach mechanically induces a negative correlation between a student's own FLFP and the average FLFP of their same-sex peers, I control for the FLFP in the student's own province of origin, $FLFP_{idc}$, or alternatively include province-of-origin fixed effects. The parameters of interest are δ^{FP} and δ^{MP}, which capture the effects of being exposed to female or male peers from provinces with one percentage point higher FLFP. While FLFP is the primary measure used here, the model is also estimated with alternative indicators introduced in Section 3.

The panel structure of the data allows me to include degree fixed effects θ_d to control for time-invariant characteristics of programs—such as typical student intake profiles—and unobserved determinants of graduate outcomes. Cohort fixed effects α_c capture factors common to all students entering university in a given year. The error term ε_{idc} contains both individual- and degree-level random components. Standard errors are clustered at

the degree level to account for potential correlation in students' outcomes within degrees. Primary outcomes include net monthly earnings, weekly hours worked, full-time employment status, and hourly wages. I also examine a range of additional labor market outcomes, such as occupational category, industry, geographic job location, and contract type. All estimations are conducted separately for male and female subsamples.

5.2 Validity of the Empirical Strategy

Threat to identification. The key identification assumption is that $\overline{FLFP}{-}i, dc^{FP}$ and $\overline{FLFP}{-}i, dc^{MP}$ are uncorrelated with time-varying unobserved factors that influence students' labor market outcomes, conditional on degree and cohort fixed effects. In other words, peer composition must evolve quasi-randomly over time within programs.

This assumption is credible in the context of Italian Master's programs, where most degrees are selective and admission is based on academic criteria—such as undergraduate GPA or entrance exam scores—and where enrollment is typically capped. In these programs, fluctuations in the geographic mix of students arise from variation in who meets the admission threshold each year, rather than from shifts in the programs themselves. Conditional on academic ability, changes in the peer group's regional composition are therefore plausibly idiosyncratic.

The concern is greater for non-selective programs, where admission is not restricted and changes in peer composition may reflect shifts in the applicant pool itself. To address this, I implement a data-driven screening strategy that flags and excludes programs exhibiting signs of non-random cohort variation—such as sharp changes in enrollment size or academic ability (see Subsection 7.1).

Other potential threats include policy changes that alter program size or admission criteria, regional labor market shocks that shift application patterns, or feedback loops whereby the composition of one cohort influences the next. I assess these risks in detail below and provide evidence that the identifying variation behaves as if random within programs over time.

Balancing tests for cohort composition. To detect selection on observables into peer groups, I perform several checks. To assess potential selection into peer groups, I conduct a series of balancing checks using predetermined student characteristics. I regress a rich set of pre-entry covariates—unaffected by peer influence but potentially correlated with unobserved student traits—on the peer FLFP variables, following equation 2. These include prior academic performance (Bachelor's and high school grades) and family background indicators (parental education and occupation). As shown in Tables XIII and XIV, none of the coefficients on peer FLFP are statistically significant, indicating

no systematic relationship between peer composition and baseline characteristics.

I complement the baseline balancing tests with two additional strategies. First, I predict students' labor market outcomes—such as labor supply and earnings—based solely on background characteristics, including age, high school type, academic grades, parental citizenship, and fixed effects for parental education and occupation. I then regress these predicted outcomes on peer FLFP exposure using the main specification (equation (2)). The idea is to test whether students with stronger or weaker expected labor market performance, based on pre-determined traits, are systematically sorted into cohorts with more gender-equal peers. As shown in Table XI, predicted outcomes are not related to peer FLFP for either gender, suggesting that cohort-level variation in peer composition is orthogonal to background-based earnings potential. Second, I regress the two treatment variables—$\overline{FLFP}{-}i, dc^{FP}$ and $\overline{FLFP}{-}i, dc^{MP}$—on the full set of predetermined covariates, controlling for degree and cohort fixed effects, and conduct joint Wald tests of significance. The resulting p-values of 0.381 and 0.221 indicate that observables do not predict exposure to more or less gender-equal peers, reinforcing the assumption of quasi-random peer composition across cohorts.

Taken together, these findings indicate that the treatment variable is unlikely to be correlated with unobserved, time-varying factors influencing labor market outcomes. Following the framework of Altonji et al., 2005, selection on observed characteristics can reasonably proxy for selection on unobservables, lending support to the identification strategy. Nonetheless, this does not completely rule out the influence of concurrent institutional changes, such as local labor market dynamics affecting cohorts. To address these concerns, I perform robustness checks (Section 7.1), including the addition of degree- and region-specific time trends and the exclusion of degrees with potentially non-random changes in size or composition, confirming the stability of the results.

5.3 Identifying Variation

A key requirement of the empirical strategy is sufficient variation in peers' geographic composition across cohorts within Master's programs. Table XII shows descriptive statistics for average FLFP in peers' provinces of origin, before and after removing degree and cohort fixed effects. The raw standard deviation is 8.50 percentage points among female peers and 8.59 among male peers. After netting out fixed effects, residual variation remains sizable—1.86 and 2.13 percentage points, respectively. While most variation reflects sorting across degrees, roughly 20–25% occurs within programs over time. This residual variation—arguably orthogonal to individual choice—is the source of identifying variation. Figure VI shows its time-series evolution across a random sample of degrees.

Importantly, this magnitude is consistent with random allocation of students across

cohorts. To validate this, I simulate 500 random assignments of students to degrees and cohorts, preserving the observed distributions of FLFP and program size. The simulated residual standard deviation of peer FLFP averages centers around 1.95 percentage points (range: 1.87–2.02), closely matching the empirical values. Figure A.III shows that deviations from average program composition follow an approximately normal distribution, further supporting the quasi-random assignment of peers conditional on controls.

Identifying variation and program's size. If variations in students' characteristics across cohorts within a degree program are truly random, then by the law of large numbers, cross-cohort fluctuations should shrink with program size. Figure VII confirms this: residualized peer FLFP is more volatile in small programs (average cohort size < 22) than in large ones (70–410 students). Table A.X complements this pattern, showing that while raw FLFP variation is stable across size quintiles, residual variation declines steadily with program size.

6 Estimates of Peer Effects

Female earnings and labor supply. Table XV reports the main estimates. Exposure to female classmates from provinces with higher FLFP increases women's labor supply at labor market entry. A one-standard-deviation increase in female peers' provincial FLFP, corresponding to 8.5 percentage points, increases weekly hours by 3.3%, raises the probability of full-time employment by 1.9 percentage points, or 2.7% relative to the mean, and increases monthly earnings by 3.7%.[28] Although the baseline specification controls for the shares of female and male international peers, the results are not sensitive to the inclusion of these controls and remain identical when they are omitted (Table A.XI).

These effects are economically meaningful. Depending on the outcome, they correspond to 33–40% of the overall gender gap and 46-76% of the gap between women raised in low- and high-FLFP environments. The effects are concentrated on the intensive margin. In contrast, peer exposure has no detectable effect on employment, consistent with the absence of gender differences in employment at labor market entry, nor does it affect survey response rates or the probability of not reporting labor market information (Table XVII), alleviating concerns about selection into the analysis sample.

Gender-specific peer effects. The effects are driven by the composition of female peers. Exposure to male classmates from higher-FLFP provinces has no detectable effect on women's earnings, hours, or full-time employment: the estimates of δ^{MP} are consistently close to zero.

[28]The estimates are virtually unchanged when I replace the student's own province-level FLFP with province-of-origin fixed effects (Table A.XII).

This asymmetry is consistent with the interpretation of provincial FLFP as a measure of the gender environment to which students were exposed before university. Section shows that origin-province FLFP predicts subsequent labor supply for women but is only weakly related to men's outcomes. As a result, variation in the composition of female peers changes exposure to classmates whose own labor market behavior is systematically associated with their childhood environments, whereas variation in the composition of male peers should be less consequential.

The pattern also accords with the structure of social interactions within Master's programs. As documented in Section 3, women discuss career plans and labor market opportunities more frequently with female than with male classmates, consistent with extensive evidence on same-gender homophily in social interaction and information transmission (McPherson et al., 2001; Currarini et al., 2009; Jackson et al., 2022).

Finally, the absence of effects from male peers weighs against partnership formation as the primary mechanism. If the estimates operated mainly through romantic matches within programs, women's outcomes might also respond to the backgrounds of male classmates, whose attitudes toward female employment and career progression may vary with their childhood environments (Fernández et al., 2004; Bursztyn et al., 2017). Consistent with the null estimates for male peers, the original survey shows that partnerships formed within Master's programs are rare (Section 10).

Female occupational choices. Table XVIII examines whether peer exposure affects occupational sorting. I classify each of the 20 occupations and 21 industries by whether their average monthly earnings and share of full-time employment are above the sample median. A one standard deviation increase in peers' provincial FLFP increases the probability of entering a high-earnings occupation by 1.7 percentage points and a high-full-time occupation by 1.6 percentage points, corresponding to increases of 4.6% and 3.1% relative to the mean. Adding occupation and industry fixed effects reduces the estimated effect on weekly hours by approximately one-third, but the remaining effect is statistically significant and economically meaningful, suggesting that occupational sorting may account for part, but not most, of the increase in women's labor supply.

Other job characteristics. The effects do not extend to other observable job characteristics. Exposure to female peers from high-FLFP provinces has no detectable effect on hourly wages (Table XV, Column 4), sector of employment, or contract type, including permanent contracts, informal employment, and self-employment (Table XIX). The evidence therefore points to changes in labor supply and occupational sorting, rather than differential access to employers or alternative employment arrangements.

Absence of peer effects on male outcomes. Table XVI reports the corresponding estimates for men. Peer exposure has no detectable effect on men's weekly hours, full-time employment, or monthly earnings.[29] The estimated effect of male peers on hourly wages is positive and statistically significant at the 10% level, and disappears after controlling for additional geographical characteristics. Because peer exposure affects women's outcomes but not men's, the gains documented for women translate directly into a 20–40% reduction in early-career gender gaps, depending on the outcome.

The absence of corresponding effects among men also provides a useful specification check. If cross-cohort variation in peers' geographical composition primarily captured common changes in program quality, applicant composition, or labor market conditions, one might expect similar patterns among men exposed to the same cohort-level changes. The gender-specific estimates weigh against such common confounding shocks, although they do not rule out unobserved factors that affect women and men differently.

Sensitivity to Alternative Measures of Peers' Background. The baseline specification uses provincial FLFP to characterize peers' childhood environments. I assess whether the results depend on this particular measure by replacing FLFP with the alternative indicators of gender equality introduced in Section 3.1. The generalized specification is:

$$Y_{idc} = \theta_d + \alpha_c + \Lambda Z_{idc} + \pi^{FP}\overline{Z}^{FP}_{-i,dc} + \pi^{MP}\overline{Z}^{MP}_{-i,dc} + \varepsilon_{idc} \tag{3}$$

where Z_{idc} denotes the alternative measure for student i's province of origin, while $\overline{Z}{-}i, dc^{FP}$ and $\overline{Z}{-}i, dc^{MP}$ denote the corresponding leave-one-out averages among female and male peers.

Table XX reports the results for log monthly earnings.[30] The estimated peer effects remain positive and statistically significant across all six contemporaneous measures of gender equality (Columns 1–6), with coefficients ranging from 0.035 to 0.041. The estimates are somewhat larger when the underlying measure captures the labor market behavior of younger women or recent cohorts of female graduates, consistent with these groups representing more salient reference points for current students. Alternative proxies based on firms' hiring preferences and historical female-to-male literacy ratios also yield positive and statistically significant estimates, although somewhat smaller in magnitude. Overall, the results are robust across measures that differ substantially in construction, data source, and time horizon, suggesting that the findings capture exposure to peers from more gender-equal childhood environments rather than a particular feature of the baseline FLFP measure.

[29] Estimates for occupational and industry outcomes are reported in Table A.XIV.

[30] Results for the remaining outcomes are qualitatively identical and available upon request.

7 Robustness and Sensitivity

This section presents three sets of robustness exercises. First, I examine whether the identifying variation coincides with changes in program characteristics or student composition that could account for the results. Second, I assess the sensitivity of the estimates to alternative sample restrictions. Third, I investigate whether provincial FLFP captures other individual or geographical characteristics of peers. For concision, the discussion focuses on log monthly earnings; estimates for the remaining outcomes are qualitatively similar and available upon request.

7.1 Robustness

The identification strategy requires that within-program variation in peers' geographical composition be orthogonal to time-varying determinants of students' labor market outcomes. Section 5.2 provided initial support for this assumption by showing, through a battery of balancing tests, that peer composition is unrelated to students' predetermined characteristics. This section further addresses potential remaining concerns that cohort-to-cohort changes in peers' geographical origins may coincide with changes in program quality, admission policies, applicant composition, or local labor market conditions.

Program-specific trends. A small share of programs exhibits smooth directional changes in geographical intake over time. To assess whether such trends drive the estimates, I augment the baseline specification with degree-specific linear time trends, so that identification relies on idiosyncratic deviations from each program's own trajectory. The estimates remain large and statistically significant and are slightly larger than the baseline estimates (Table XXI), indicating that smooth compositional trends do not drive the results. Similarly, allowing for region-specific linear time trends yields very similar conclusions (Table XXII).[31]

Non-random changes in peers' composition. A second concern is that changes in peers' geographical origins reflect shifts in admission policies or applicant selection rather than quasi-random fluctuations. Because admission policies are not directly observed, I adopt a data-driven approach to identify programs exhibiting unusually large changes in student composition over time.

I first exclude degree programs displaying statistically significant trends in cohort size (at the 10% level), eliminating approximately one-quarter of all programs. The estimated peer effects remain statistically significant and, if anything, become larger (Table XXIII).

[31] Restricting the analysis to the balanced panel of Master's programs observed in every cohort, which comprises 85% of all programs, also leaves the estimates largely unchanged. Results are available upon request.

More importantly, I exclude degree programs exhibiting statistically significant trends in the average geographical composition of their students, as measured by the FLFP of their provinces of origin. The estimates remain large and statistically significant and are slightly larger than the baseline estimates (Table XXIV).

I next examine whether programs experience unusually large cohort-to-cohort changes in predetermined characteristics that may signal non-random shifts in student composition. Specifically, I consider three variables: (i) the average Bachelor's final grade, capturing average student ability; (ii) the standard deviation of Bachelor's grades, capturing the dispersion of ability; and (iii) cohort size. After residualizing each variable with respect to degree and cohort fixed effects, I compute, for each degree, the average absolute cohort-level deviation:

$$Z_d^Y = \frac{1}{T_d} \sum_{t=1}^{T_d} \left| r_{dt}^Y \right| \tag{4}$$

where r_{dt}^Y denotes the residualized cohort average of characteristic Y, and T_d is the number of cohorts observed for degree program d. I normalize each Z_d^Y by dividing it by the average value of Y across cohorts and progressively exclude programs exhibiting the largest fluctuations along each dimension. The estimated peer effects remain remarkably stable throughout and continue to be statistically significant even when restricting the sample to programs with very limited cohort-to-cohort variation in student ability or cohort size (Table XXV).

Taken together, these results suggest that the estimated peer effects are unlikely to be driven by systematic changes in program quality or the composition of admitted students.

7.2 Sensitivity

This subsection examines whether the estimated peer effects are sensitive to alternative sample restrictions that affect either the plausibility of the identifying assumption or the intensity of peer interactions. Table XXVI reports the results. Across all specifications, the estimated effects remain positive and broadly similar to the baseline, reinforcing the robustness of the main findings.

Cohort size. I first examine whether the estimates vary with the size of the Master's program. Excluding programs in the bottom decile of the cohort-size distribution leaves the estimates virtually unchanged (Column 2), indicating that the results are not driven by noise in very small programs. Excluding instead the largest programs produces slightly larger estimates (Column 3). Splitting the sample at the mean cohort size (Columns 4–5) shows that peer effects are concentrated in smaller programs: the estimates remain large and statistically significant below the mean, but become substantially smaller and statis-

tically insignificant above it. Restricting further to the largest programs only (Column 6) yields small and insignificant estimates. This pattern is consistent with the fact that cross-cohort variation in peer composition is more limited in larger programs. In addition, larger programs may feature more fragmented social networks, reducing the scope for peer interactions at the cohort level.

Proportion of students with a Bachelor's from the same institution. I next consider whether results depend on the extent to which students share a common undergraduate background. In programs where a large share of students completed their Bachelor's at the same institution, cohort composition may be more predictable due to shared academic trajectories. Excluding programs with a very high concentration of same-institution students (Column 7) leaves the estimates unchanged. Restricting further to programs in the lower tail of this distribution (Column 8), where peer composition is plausibly more idiosyncratic, yields even larger effects. This suggests that the results are not driven by settings in which students can more easily anticipate the geographic composition of their peers.

International students. I next assess whether the presence of international students affects the estimates. Peer composition is measured using Italian students only, while controlling for the share of international students in the cohort. This implicitly assumes that relevant peer interactions are primarily among Italian-born students, which may be restrictive in more internationally diverse programs. Restricting the sample to programs with no international students (Column 9) yields larger estimated effects, while allowing for a small share of international students (Column 10) produces estimates very close to the baseline. This indicates that the main results are not driven by measurement issues in peer composition, and are if anything stronger in more homogeneous cohorts.

Pre-existing ties and origin-based networks. The estimated effects may depend on students' opportunities to form relationships outside pre-existing or geographically concentrated networks. I therefore examine heterogeneity according to three measures of potential network isolation. First, I compare students who are the only member of their cohort from their province of origin with those who have at least one classmate from the same province. Second, I allow the effects to vary with the number of same-province classmates, distinguishing students with relatively few such peers from those embedded in larger origin-based groups. Third, I compare students who are the only member of their cohort from their high school with those who attended the same high school as at least one classmate. If students with access to pre-existing or geographically concentrated networks interact disproportionately within these groups, exposure to the broader composition of

the cohort should matter more for students who lack such ties. Accordingly, the estimated peer effects should be larger among students who are isolated by province or high school and among those with fewer same-province classmates.

7.3 Which Peers' Characteristics Matter?

Exposure to female classmates from high-FLFP provinces increases women's earnings and hours worked. Do these effects reflect peers' gender-related childhood environments, or other individual and geographical characteristics correlated with those? This section distinguishes between these explanations by examining alternative peer characteristics and features of peers' provinces of origin.

Other peer characteristics. Selection into Master's programs may vary by province of origin, generating systematic differences between students from high- and low-FLFP provinces. The estimated peer effects could therefore reflect classmates' academic preparation, family background, or other characteristics rather than the gender-related environments in which they were raised. To test for this possibility, I augment the baseline specification with a set of controls for all these other characteristics of peers. The estimated effect of peers' provincial FLFP remains stable when I control for the shares of classmates with above-median bachelor's grades, an academic-track high school background (*liceo*), working mothers, college-educated parents, or parents in high-status occupations (Table XXVII). Furthermore, adding cohort size and the female share of the cohort similarly leaves the estimate unchanged. Observable differences in peer quality, family background, and cohort composition therefore do not drive peer effects.

Alternative geographical characteristics. As shown in Section 3, provincial FLFP is correlated with other local characteristics. Provinces with higher FLFP tend to have higher per capita income, greater educational attainment, and higher male labor force participation. The baseline estimates could therefore reflect exposure to peers from more economically developed or highly educated areas rather than to peers from more gender-equal environments. To assess this possibility, I augment the baseline specification with characteristics of peers' provinces of origin, including per capita income, municipality size, urbanization, sectoral composition, fertility, educational attainment, and male labor force participation. The estimated effect of peers' FLFP remains stable as these controls are added (Table XXVIII). Controlling for male labor force participation reduces precision because of its high correlation with FLFP, but leaves the point estimate largely unchanged. Moreover, male labor force participation is not significantly associated with women's labor market outcomes once FLFP is included.

As a complementary exercise, I replace peers' provincial FLFP with each alternative

geographical characteristic in turn. None produces a systematic pattern of effects on women's labor market outcomes (Table XXIX). The absence of comparable relationships for these alternative characteristics supports the interpretation that the baseline effects reflect peers' gender-related childhood environments rather than other observed attributes of their provinces of origin.

8 Asymmetry in Peer Effects

The linear-in-means model presented in equation 2 assumes that a student's outcome is a linear function of her peers' average background characteristics and that this relationship is homogeneous across students' own types. These assumptions rule out potentially important forms of non-linearity: students may respond differently depending on their own backgrounds, and outcomes may depend on features of the peer distribution beyond its mean. A growing empirical literature documents departures from the linear-in-means model along these dimensions (Boucher et al., 2024).[32] The distinction is not merely technical: understanding non-linearities in peer effects is central to translating peer-effect estimates into the design of reassignment policies (S. E. Carrell et al., 2013). Under homogeneous linear-in-means peer effects, reallocating a fixed population of students across equally sized groups leaves average outcomes unchanged. When peer effects are nonlinear, by contrast, the allocation of students across groups can affect aggregate outcomes, potentially creating scope for welfare-improving reassignment.

To examine whether peer effects vary with students' own childhood environments, I summarize peer exposure using the share of classmates from above-median-FLFP provinces and allow its effect to differ across students' own FLFP quartiles. Each student is assigned to a quartile based on the distribution of provincial FLFP rates within the sample. For each degree-cohort, I then compute the leave-one-out shares of female and male peers originating from provinces with above-median FLFP. I interact the share of female peers from above-median-FLFP provinces with indicators for the student's own FLFP quartile, while including the corresponding share of male peers additively. The specification therefore allows the effect of female peer exposure to vary across students' own backgrounds. All specifications include degree and cohort fixed effects. The estimating equation is:

[32] Examples include C. Hoxby and Weingarth (2005), S. Carrell et al. (2009), Mas and Moretti (2009), Hanushek and Rivkin (2009), Lavy et al. (2012), Imberman et al. (2012), Burke and Sass (2013), Booij and Leuven (2017), Feld and Zölitz (2017), Michelman et al. (2022), Cattan et al. (2025), and Tincani (2026).

$$
\begin{aligned}
Y_{idc} = \theta_d + \alpha_c + \beta_2 \mathrm{Q2}_{idc} + \beta_3 \mathrm{Q3}_{idc} + \beta_4 \mathrm{Q4}_{idc} \\
+ \gamma_1 \mathrm{ShareAbm}^{FP}_{-i,dc} + \gamma_2 \mathrm{ShareAbm}^{FP}_{-i,dc} \times \mathrm{Q2}_{idc} \\
+ \gamma_3 \mathrm{ShareAbm}^{FP}_{-i,dc} \times \mathrm{Q3}_{idc} + \gamma_4 \mathrm{ShareAbm}^{FP}_{-i,dc} \times \mathrm{Q4}_{idc} \\
+ \pi \mathrm{ShareAbm}^{MP}_{-i,dc} + \varepsilon_{idc}. \qquad (5)
\end{aligned}
$$

Figure VIII reports the estimated effect of a one-standard-deviation increase in the share of female peers from above-median-FLFP provinces, separately by the student's own FLFP quartile. The effects exhibit a marked asymmetry across student backgrounds. Women originating from the bottom two quartiles experience substantially larger gains than women from more egalitarian environments. A one-standard-deviation increase in the share of high-FLFP female peers—equivalent to 36 percentage points, or to replacing approximately nine low-FLFP female peers with high-FLFP female peers in the average cohort—raises the probability of full-time employment among women in the first and second quartiles by approximately 3 percentage points. The corresponding effects for women in the third and fourth quartiles are close to zero. Women from less egalitarian environments therefore have substantially greater scope to benefit from exposure to female peers raised in high-FLFP areas.

Peer influence and childhood background. The empirical model in equation 5 provides a framework for comparing the magnitude of peer effects with outcome differences associated with students' childhood environments. Because the female peer-share measure is standardized and centered at zero, β_4 captures the average difference in outcomes between women from the most egalitarian (Q4) and least egalitarian (Q1) provinces of origin, evaluated at the mean level of peer exposure ($\approx 41\%$ of female peers from above-median-FLFP provinces). A one-standard-deviation increase in the share of female peers from high-FLFP provinces changes the Q4–Q1 gap from β_4 to $\beta_4 + \gamma_4$, where γ_4 captures the extent to which peer exposure narrows or widens the difference associated with students' own backgrounds. Table XXX reports the corresponding coefficients for all quartiles.

The estimates indicate that exposure to high-FLFP female peers substantially narrows outcome differences associated with students' childhood environments. A one-standard deviation increase in the share of female peers from high-FLFP areas reduces the Q3–Q1 difference in weekly hours by 65% and the Q4–Q1 difference by 58% and fully closes the gap in full-time work. Peer interactions during graduate study can therefore substantially attenuate labor market disparities associated with growing up in less egalitarian

environments.

9 Mechanisms

A central challenge in the empirical literature on peer effects is to identify the mechanisms through which peers affect individual outcomes (Sacerdote, 2011; Feld and Zölitz, 2017; Barrios Fernandez, 2023). This has proved difficult because the administrative data typically used to estimate peer effects record realized outcomes but provide little information on individuals' preferences, aspirations, beliefs, or social interactions. Yet distinguishing among mechanisms is important for policy: the same reduced-form peer effect may call for very different interventions depending on whether peers expand individuals' economic opportunities or change how those opportunities are perceived and evaluated. Identifying the relevant channels may therefore help design policies that reproduce some of the benefits of peer exposure without deliberately manipulating peer-group composition.

The peer effects documented above may operate through two conceptually distinct, though not mutually exclusive, classes of mechanisms. First, peers may expand women's objective economic opportunities by improving their human capital and academic credentials, facilitating geographical mobility toward better labor markets, or providing access to jobs through referrals and professional connections. These mechanisms alter the set of opportunities available to women. Second, peers may affect women's aspirations, preferences, and beliefs without changing their qualifications or objective access to jobs. Exposure to classmates raised in more gender-egalitarian environments may change what women perceive as attainable and how they evaluate different job attributes, thereby affecting the jobs for which they search and apply. This second class of mechanisms changes women's objectives or beliefs about their opportunity set rather than the opportunity set itself.

I use the unusually rich combination of administrative and survey data to distinguish between these classes of mechanisms. I first test the leading channels through which peers could expand women's objective economic opportunities: improvements in academic credentials, geographical mobility toward better labor markets, and access to local labor market connections. I then examine whether peers instead change how women perceive and evaluate the opportunities available to them. For this purpose, I combine stated job preferences from the institutional pre-graduation survey with detailed measures of expectations, perceived constraints, gender attitudes, and social interactions from my original survey.

9.1 Human Capital and Access to Labor Market Opportunities

Human capital. I first examine whether exposure to peers from high-FLFP provinces affects academic performance. I re-estimate the baseline specification using GPA, final graduation grade, time to degree, and delayed graduation status (*fuoricorso*) as outcomes. Peer exposure does not affect any of these measures, with precisely estimated effects close to zero throughout (Table XXXI, Panel A). For example, the 95% confidence interval rules out an increase in GPA exceeding 0.10 points following a one-standard-deviation increase in female peers' provincial FLFP—less than 0.4% of the average GPA. Because grades constitute the primary academic credentials visible to employers, these results rule out improvements in observed academic performance and credentials as the primary channel behind the subsequent labor market effects.

Geographical mobility. Peers may also expand women's opportunities by shaping where they search for and accept jobs. Exposure to students from other provinces could provide information about geographically distant job opportunities or reduce the costs of moving through cohort-based social ties. I therefore examine whether peer composition affects FLFP in the province of employment or the probability that women work outside their province of birth or their province or region of study. The estimates show no systematic relationship between peer composition and any of these outcomes (Table XXXI, Panel B). The labor market effects therefore do not operate through geographical sorting toward more favorable local labor markets. One interpretation of this null effect is that the relevant location decision often occurs before labor market entry: approximately 70% of graduates work in the same region in which they attended university. Graduate enrollment may therefore anchor students to a local labor market, leaving less scope for peers to affect their subsequent geographical location.

Local labor market connections. Peers could also expand women's employment opportunities through direct referrals or access to professional networks, a channel documented in several other settings.[33] This mechanism is less likely to operate in this setting than in contexts in which network members are already established in the labor market. Classmates typically graduate and begin searching for work at approximately the same time and therefore have limited scope to refer one another to their employers at labor market entry. They may nevertheless facilitate access to pre-existing local connections. Given that most graduates work in the region in which they attended university, students originating from that region may be better connected to local employers through

[33]Examples include Zimmerman (2019), Michelman et al. (2022), Einiö (2025), Campa (2025), and Hampole et al. (Forthcoming).

their families or broader social networks and may facilitate access to these connections for nonlocal classmates.

Although the absence of firm identifiers prevents a direct test of referrals, I assess this local-connections channel by augmenting the baseline specification with the shares of female and male peers originating from the university's province or region. The estimated effect of female peers' FLFP remains essentially unchanged (Table XXXII). The baseline effect is therefore not explained by differential exposure to classmates with plausibly stronger pre-existing connections to the local labor market. Together with the fact that classmates enter the labor market at approximately the same time, this evidence makes direct referrals an unlikely primary mechanism. It does not, however, rule out the transmission of information about vacancies or job-search strategies.

9.2 Sociological Mechanisms: Aspirations, Information, and Beliefs

The preceding evidence provides little support for the leading mechanisms through which peers could expand women's objective economic opportunities. Peer exposure improves labor market outcomes without detectable changes in women's academic credentials, geographical location, or exposure to classmates with stronger local labor market connections. These results point toward a different class of mechanisms: peers may change how women perceive and evaluate the opportunities already available to them.[34]

Such mechanisms are typically difficult to study because administrative data reveal realized choices but provide little information on the preferences, aspirations, and beliefs underlying them. The institutional pre-graduation survey provides unusual leverage on these channels by eliciting students' preferences over job attributes shortly before they enter the labor market.

Preferences over job attributes. Differences in the valuation of workplace attributes are an important determinant of early-career gender gaps among college graduates. Women typically place greater value on nonpecuniary attributes such as flexible hours, part-time work, and job stability, whereas men place greater value on earnings growth; these differences account for a substantial share of the early-career gender earnings gap (Bursztyn et al., 2017; Wiswall and Zafar, 2018).[35]

The institutional survey asks students to rate the importance of several job attributes

[34]This interpretation parallels recent work showing that exposure effects can operate through social interactions, role models, aspirations, and norms rather than through changes in economic resources or general human capital alone (Bell et al., 2019; Chetty et al., 2026).

[35]Differences in job preferences have also been documented in other segments of the labor market. See, for example, Mas and Pallais (2017), Le Barbanchon et al. (2021), Caldwell and Oren (2024), and Caldwell et al. (2026).

on a scale from 1 (low) to 5 (high). I use these responses to construct two standardized indices: one capturing preferences for pecuniary attributes, including earnings and career advancement, and another capturing preferences for temporal flexibility, including flexible working hours and leisure time. Each index is the unweighted average of its constituent items and is standardized to have mean zero and standard deviation one. I also construct an indicator for assigning the highest possible importance to a job's social utility, an attribute over which women and men differ substantially.

Table XXXIII provides evidence of modest but systematic changes in women's stated job preferences. A one-standard-deviation increase in female peers' provincial FLFP reduces the preference for temporal flexibility by 0.027 standard deviations and lowers the probability of assigning maximum importance to a job's social utility by 1.2 percentage points, or 3% relative to the sample mean. Although quantitatively modest, both effects indicate that peer exposure shifts women's preferences away from job attributes disproportionately valued by women and in a direction consistent with the subsequent increase in full-time employment and hours worked.

10 Evidence from a New Data Collection

To further investigate the mechanisms underlying my findings, I designed a novel survey with three objectives: (1) to explore variations in women's beliefs based on their childhood exposure to female labor force participation; (2) to assess the influence of these beliefs on job acceptance decisions; and (3) to examine how these beliefs are updated over time.

Design. While a growing body of research has documented the intergenerational persistence of cultural norms—often using the epidemiological approach based on ancestral culture—these studies typically remain agnostic about the specific beliefs driving this persistence.[36] This survey contributes to filling this gap by directly eliciting a broad set of beliefs and expectations potentially relevant for women's labor supply decisions. The survey was initially designed to capture attitudes and social norms related to gender roles, as well as expectations regarding fertility and motherhood-related career interruptions (so-called *child penalties*). However, insights from a prelim1inary qualitative phase—consisting of 25 in-depth interviews with students from various universities—highlighted additional, previously underexplored considerations. In particular, respondents from less egalitarian regions frequently mentioned a perceived scarcity of full-time job opportunities for women, often attributed to employers' assumptions about future childcare responsibilities. Motivated by these findings, the final version of the questionnaire was expanded to

[36] One exception is Bursztyn et al., 2020, which identifies biased second-order beliefs among men—regarding the social acceptability of women working outside the home—as a key constraint on female labor force participation in Saudi Arabia.

include measures of labor market expectations, such as beliefs about job availability and anticipated employer discrimination. The survey was structured to track these beliefs over time.

10.1 Survey Administration

The survey was conducted among graduate students enrolled at the University of Bologna, the largest university in the country, accounting for approximately 7% of all national graduates. Importantly, it attracts students from diverse cultural backgrounds, with 88.8% and 69.6% of participants coming from different provinces and regions, respectively.

To construct the analysis sample, I randomly selected a subset of Master's programs and, within each, randomly chose one first-semester course from the first year and one from the second year. Students attending these courses were invited to participate in the survey. The survey was administered in person during class time. Specifically, with lecturers' consent, I visited each class—typically during the first or last 15 minutes—and invited students to voluntarily complete a 10-minute questionnaire via their mobile devices using the SurveyMonkey platform. Prior to administration, I provided general information about the study.[37] To encourage participation, students were offered entry into a lottery with three prizes, each consisting of €100 gift cards.[38] The response rate among attending students was approximately 97%.[39] Importantly, students were not informed in advance about the survey administration to ensure that attendance during the intervention was exogenous to the survey, thereby mitigating selection concerns.

The survey took place between November 2023 and February 2024. I chose to run the survey 3-4 months after the start of the academic year to strike a balance between students being able to give informed responses to the questions—especially about the program's social environment— and learning of students in the first year being not yet complete. A total of 899 students from 34 Master's programs participated in the survey. Among them, 535 identified as women, 348 as men, and 13 as non-binary. The sample included 571 students in their first year and 322 in their second year. This disparity is attributed to the curriculum structure, with mandatory courses mainly offered in the first year. Consequently, the second-year cohort tends to be smaller due to the greater flexibility in choosing optional courses.

[37]Students were informed that the questionnaire focused on their beliefs and labor market expectations as part of a study on post-college career decisions. To avoid priming, the connection to peer influence or gender inequalities was not disclosed.

[38]The gift cards were generic and redeemable across multiple providers to minimize selection bias related to gift choice.

[39]Self-reported attendance data from the AlmaLaurea survey indicates that around 77% of students attend classes regularly.

10.2 Sample Selection and Description

I exclude from the sample students participating in the Erasmus program or enrolled in a Bachelor's program (less than 1%), as well as those with missing information on their country or province of origin (5.8%). The final sample comprises 490 female students, with 319 in the first year and 171 in the second year of their Master's programs.

Summary statistics for the full sample and subgroups defined by the FLFP rate in students' province of origin are presented in Table XXXIV. Compared to the main sample, this sample overrepresents students from higher socioeconomic backgrounds, as indicated by a greater share of parents with university degrees, and includes more students from provinces with higher FLFP rates. Additionally, the sampled programs have a larger proportion of students who migrated from other provinces or regions. Finally, the distribution of fields of study differs: disciplines such as engineering, architecture, healthcare, and psychology are absent, while the humanities are overrepresented.

A comparison of women from high- and low-FLFP provinces of origin reveals differences in the role models present within their families. Students from low-FLFP provinces are more likely to have fathers with higher education levels than their mothers, whereas the reverse is true for students from high-FLFP areas. Additionally, mothers in low-FLFP provinces are more likely to have experienced significant career interruptions—so-called *child penalties*—during their children's early years. Despite these background differences, the two groups are similar in several important respects. Just under 50% of students in both groups report being in a couple, though only a small fraction have partners within the same Master's program. Furthermore, their fertility expectations and job-search intentions are broadly comparable.

10.3 Expectations About The Job Offer Distribution

This section investigates how students' expectations about the job offer distribution vary by background and are shaped by learning. The hypothesis is that women raised in regions with weaker female labor market conditions may hold more pessimistic beliefs about the frequency of job offers, particularly with regard to full-time versus part-time work. To test this, I elicit students' expectations about two key parameters of a job search model: (i) the overall arrival rate of job offers, and (ii) the relative frequency of part-time versus full-time offers. Beliefs are collected using the hypothetical scenarios described in Box 10.3. The design builds on a random search framework, which provides a tractable way to identify the primitives of interest.[40]

[40] Although the random search model abstracts from endogenous application behavior, its insights extend to directed search frameworks, in which beliefs about offer probabilities influence both application targeting and search effort. In both settings, differences in beliefs can shape behavior and contribute to unequal outcomes.

Expectations are elicited by fixing the number of job applications at ten, which allows for isolating perceptions about the likelihood of receiving job offers, abstracting from heterogeneity in expected search effort. Restricting the hypothetical applications to jobs in the student's field of study narrows the occupational set and enhances comparability across respondents.

Since realized labor market outcomes are not observable for this prospective sample, I also collect students' stated intentions to accept part-time job offers. Following the approach of Wiswall and Zafar, 2021, these intentions are measured using a stated probabilities method rather than a discrete choice format. This technique captures the uncertainty students face when reporting their likely decisions.[41]

Elicitation of Job Offer Arrival Rates

1. *Consider the following scenario: you have graduated from the Master's program in which you are currently enrolled and you start searching for a job. You submit 10 applications to positions aligned with your field of study. When applying, you don't know the specific working conditions—such as the monthly salary or whether the contract is part-time or full-time*[a].

- Out of these 10 applications, how many job offers do you expect to receive? ($\boldsymbol{\alpha}$) Provide your answer on a scale from 0 to 10.

- You receive your first job offer. What do you believe is the probability that the employer will offer you a part-time contract (less than 28 hours/week)? ($\boldsymbol{\gamma}$) Provide your answer on a scale from 0 to 100.

2. *While waiting for responses to your applications, an employer contacts you and offers a part-time position (28 hours/week) with a net monthly salary in line with your expectations. You must decide whether to accept the offer or turn it down and wait for responses from the other applications.*

- What is the probability that you would accept this part-time job offer? Provide your answer on a scale from 0 to 100.

[a]Note that in Italy, 91% of online job postings do not include salary or salary ranges, and precise information about working hours is often limited (Burning Glass data)

Asymmetries in baseline beliefs. Table XXXV, Panel (a), presents an analysis of students' baseline beliefs, elicited during the first year of their program-prior to substantial peer interaction-to capture initial heterogeneity shaped by pre-college environments. The table compares beliefs between students from provinces with below- versus above-

[41]A discrete choice model is a lim1iting case of the stated probability framework—one in which individuals have no uncertainty, and would assign a probability of exactly 1 (certain acceptance) or 0 (certain rejection) to the job offer. However, the data reject this assumption: only 4.83% of students report a probability of 1, and fewer than 1% report a probability of 0.

median FLFP. Each belief (rows) is regressed on a binary indicator for high-FLFP origin, controlling for field of study fixed effects. The estimates reveal systematic differences in expectations by province of origin. First, women from low-FLFP provinces expect marginally fewer job offers: among ten submitted applications, they anticipate receiving 3.21 offers on average, compared to 3.52 among their high-FLFP counterparts, though this difference is not statistically significant. More notably, a substantial and significant gap emerges in their expectations regarding the proportion of part-time job offers. Women from low-FLFP areas expect a 6.45 percentage point higher likelihood that an offer will be part-time rather than full-time—equivalent to a 12.6% increase relative to the high-FLFP group. Consistent with these expectations, they are also 7 percentage points more likely to report that they would accept a part-time offer, a difference of similar magnitude (12%). These asymmetries persist after controlling for students' background characteristics (e.g., age, parental education), job search intentions, and expected job location, as shown in Table XXXVIII. In addition, field-of-study fixed effects mitigate concerns that the differences reflect sorting into distinct occupational tracks.

Beliefs updating. Panel (b) of Table XXXV analyzes how beliefs evolve over time by examining responses from second-year students. Overall, the results indicate convergence in beliefs across students from low- and high-FLFP provinces, consistent with a process of learning. In particular, the initially large gap in expectations about the likelihood of receiving a part-time job offer narrows by more than 70% between the first and second years. Further evidence supporting the learning interpretation comes from changes in the within-field dispersion of beliefs. Across degree programs, the standard deviation in students' expectations about part-time job offers is 24.28 in the first year, declining by over one-third in the second year. Importantly, belief updating is strongly asymmetric, mirroring the heterogeneity in peer effects. Women from low-FLFP provinces revise their expectations downward by more than 5 percentage points—a 9% decrease—while women from high-FLFP provinces exhibit no significant change. This asymmetry in updating could be consistent with prior differences in information sets. Students from low-FLFP areas likely form their initial beliefs based on labor markets that differ substantially from the ones in which they now expect to work, as implied by their intended job location (Table XXXIV), while such discrepancy is less pronounced for their high-FLFP counterparts. While the data do not permit a causal identification of peer effects, the stark downward revision among low-FLFP students—coupled with the stability among their high-FLFP peers—suggests that peer-driven information transmission is a plausible mechanism behind belief updating.

10.4 Beliefs and Job Search: an Illustrative Model

How does heterogeneity in beliefs translate into differences in economic outcomes? To illustrate this relationship, I develop a stylized job search model in the spirit of McCall (1970), in which risk-neutral female graduates search for their first post-graduation job. The model abstracts from geographical origin in the baseline setup, allowing for a clean exposition of the core mechanism. I later introduce heterogeneity in key parameters to capture differences between women from high- and low-FLFP provinces, with a focus on implications for part-time job acceptance.

Model setup. Consider an economy where three states exists: an individual can be unemployed, employed in a part-time job or employed in a full-time job. Both part-time (P) and full-time (F) jobs involve fixed weekly hours. I denote the number of hours in a part-time job as $h^P = \theta h^F$, with $\theta < 1$. Time is discrete, and all individuals discount the future at a constant rate $\beta \in (0, 1)$. Individuals are risk-neutral and derive utility solely from income. Their preferences are represented by a simple linear utility function over consumption, u(c) = y, implying that they seek to maximize expected lifetime labor income. I abstract from other sources of income, so that instantaneous income is given by:

$$y = \begin{cases} y^F & \text{if employed in full-time job} \\ y^P & \text{if employed in part-time job} \\ b & \text{if unemployed} \end{cases}$$

Unemployed individuals receive an instantaneous utility of b, which reflects any income or value associated with not working, such as the pecuniary value of leisure or unemployment insurance (UI) benefits. y_P and y_F denote the total per-period income associated with part-time and full-time employment, respectively. For simplicity, I normalize the number of hours in a full-time job to one, so that $y_F = w$ and $y_P = \theta w$.

Each period, unemployed job seekers receive job offers with probability α^*. A fraction γ^* of these offers are part-time positions. Each job offer includes a wage drawn from a distribution F(w), which has support and non-zero density on $[w_{\min}, w_{\max}]$. To simplify the analysis, I assume that the wage distribution is the same for part-time and full-time offers. Upon receiving a job offer, individuals decide whether to accept the offer and exit unemployment, or reject it and continue searching while enjoying the value of leisure b. I assume that employment—both part-time and full-time—is an absorbing state, i.e. there is no job destruction and no on-the-job search. I further assume that the environment is stable, i.e. that the arrival rates of full-time and part-time job offers

do not change over the course of the search spell. Individuals are infinitely lived and, therefore, the model is stationary. Throughout the analysis, I use an asterisk * to denote true, objective probabilities of job offer arrival. This notation distinguishes actual labor market parameters from individuals' subjective beliefs, which may differ from the truth.

Workers' beliefs. I begin by assuming that workers make decisions under potentially limited information regarding job offer arrival rates. In particular, workers may not know the true per-period probability of receiving a job offer, α^* or the true proportion of part-time job offers, denoted by γ^*. Let α_t and γ_t represent the worker's subjective beliefs about these parameters. Beliefs are biased if $\alpha_t \neq \alpha^*$ or $\gamma_t \neq \gamma^*$. While beliefs potentially evolve over time due to learning, in this version of the model I abstract from this possibility and assume that α and γ are not time-varying. Workers take their decisions on whether to accept job offers based on their subjective beliefs α and γ. I abstract away from other potential biases in beliefs, for example on the wage offer distribution F(w), that I assume to be commonly known to all individuals.

Perceived values of employment and unemployment. I now characterize the perceived flow values of unemployment and employment.[42] For a worker with beliefs α and γ, the perceived value of unemployment equals

$$\begin{aligned} U(\alpha,\gamma) = b + \beta\alpha\Bigg[\gamma \int_{y_P} \max\{V(y_P), U(\alpha,\gamma)\}\, dG(y_P) \\ + (1-\gamma)\int_{y_F} \max\{V(y_F), U(\alpha,\gamma)\}\, dG(y_F)\Bigg] \\ + \beta(1-\alpha)U(\alpha,\gamma) \end{aligned} \tag{6}$$

The values of part-time and full-time employment at wage w are respectively

$$V(y_P) = y_P + \beta V(y_P) \rightarrow (1-\beta)V(y_P) = \theta w \tag{7}$$

$$V(y_F) = y_F + \beta V(y_F) \rightarrow (1-\beta)V(y_F) = w \tag{8}$$

Reservation wages. A job-seeker's decision to accept a job offer is determined by the reservation wage property: each job offering wages above the reservation value is accepted. The job seeker determines her reservation wage in order to maximize their perceived continuation value at any point during the search spell. I define the reservation earnings, $R(\alpha,\gamma)$, as the total per-period income at which a job seeker is indifferent

[42] These values are "perceived" in the sense that they are based on the worker's subjective beliefs about the arrival rates of job offers rather than the true underlying probabilities.

between accepting a job and remaining unemployed. The resulting expression for the reservation earnings equals

$$V(R(\alpha,\gamma)) - U(\alpha,\gamma) = 0 \rightarrow R(\alpha,\gamma) = (1-\beta)U(\alpha,\gamma) \tag{9}$$

Because part-time and full-time jobs differ in the number of working hours, the reservation earnings condition expressed above is verified for two different reservation wages, separately for the two job types. I define the reservation wages for part-time and full-time jobs as $w_{R,P}(\alpha,\gamma)$ and $w_{R,F}(\alpha,\gamma)$. The expressions are

$$w_{R,P}(\alpha,\gamma) = \frac{R(\alpha,\gamma)}{\theta} \quad \text{and} \quad w_{R,F}(\alpha,\gamma) = R(\alpha,\gamma) \tag{10}$$

Any part-time or full-time job offering wages above these values is accepted. Reservation wages are determined based on workers' beliefs regarding α^* and γ^*, as illustrated in the following propositions.

Proposition 1. *Ceteris paribus, reservation wages are increasing in beliefs α.*
Proposition 2. *Ceteris paribus, reservation wages are decreasing in beliefs γ.*

Heterogeneous beliefs and model's predictions. Although all individuals face the same objective job offer arrival rates, I allow for heterogeneity in beliefs. Let (α_L, γ_L) and (α_H, γ_H) denote the subjective beliefs held by women from low- and high-FLFP regions, respectively. Empirical evidence from the previous section indicates that women from low-FLFP provinces expect both fewer job offers and a higher proportion of part-time opportunities. Formally:

$$\alpha_L < \alpha_H \quad \text{and} \quad \gamma_L > \gamma_H \tag{11}$$

By Propositions 1 and 2, these beliefs imply lower reservation earnings among women from low-FLFP regions, leading to a greater likelihood of accepting part-time employment. Figure IX illustrates a strong relationship between students' subjective expectations about the prevalence of part-time job offers and their willingness to accept such offers. Estimates from a simple linear regression indicate that a one standard deviation increase (23 percentage points) in the expected probability of receiving a part-time offer results in an approximately 8 percentage point increase in the acceptance rate of part-time jobs, representing more than a third of the standard deviation in the sample, and this is robust

to the inclusion of field fixed effects (Table XXXIX).

10.5 Fertility and Gender Attitudes

Expectations about fertility and future child penalties. In Italy, child penalties-reductions in labor supply following childbirth-vary sharply by region (**lattanzio**). These regional disparities may shape women's beliefs about their own future trajectories: those from less gender-equal contexts may expect children at younger ages or anticipate larger employment losses associated with motherhood, and may respond by selecting into more flexible jobs in anticipation of motherhood (as in Adda et al., 2017). This section tests whether women from high- and low-FLFP areas hold systematically different expectations about fertility timing and the career costs of children (elicitation is described in Box 10.5).

Table XXXVI presents the main results. At baseline, women from low-FLFP provinces are slightly less likely to expect to have children in the future and anticipate doing so at a marginally later age compared to their peers from high-FLFP provinces. More importantly, they are less likely to foresee reductions in working hours due to motherhood and more likely to expect to remain employed full-time during the early years of parenthood. This pattern holds across both unconditional expectations (Scenario 1) and conditional expectations in the presence of full-day childcare near their residence (Scenario 2). For both groups, childcare availability significantly shifts anticipated labor supply: the share of women expecting to work full-time increases by 43%–58% with access to full-day childcare. One year later, both groups revise their expectations upward, especially under the childcare-available scenario. Approximately 80% of women in each group now expect to work full-time during the early years of motherhood. Two things emerge from this analysis. First, women from low-FLFP areas do not anticipate higher career costs of motherhood. This may reflect misperceptions about the magnitude of child penalties (as in Kuziemko et al., 2018), positive selection in the sample, or shifts in the magnitude of child penalties themselves. Second, in contrast to the asymmetric updating observed for job offer beliefs, expectations related to motherhood and future employment evolve symmetrically across both groups, which mitigates concerns that students from high-FLFP areas are generally more resistant to belief updating.

Elicitation of Fertility Expectations

1. Would you like to have children in the future? *Yes / No / Don't know / Already have*
2. At what age do you expect to have your first child?
3. Expected labor supply at motherhood:
   - ***Scenario 1***. *Suppose that your partner is earning enough to support your family. What do you think you will do when your child is young (0–2 years)?*
     Answer: *No work / Work part-time / Work full-time*
   - ***Scenario 2***. *Suppose that your partner is earning enough to support your family and that in the area you live a full-day place in childcare is available to you. What do you think you will do when your child is young (0–2 years)?*
     Answer: *No work / Work part-time / Work full-time*

Gender attitudes. The survey also elicits women's attitudes toward employer discrimination and societal expectations regarding gender roles. Respondents were asked to indicate their agreement with two statements: "Employers prefer to hire men for full-time jobs" and "A woman is negatively judged in society if she is too ambitious," using a Likert scale ranging from strongly disagree to strongly agree.

Table XXXVII compares responses across students from provinces with above- and below-median FLFP, controlling for field of study. Several patterns emerge. First, in both groups, a majority of women perceive gender-based discrimination in hiring and believe that ambitious women face social scrutiny. However, at baseline, women from low-FLFP areas are more likely to agree or strongly agree with these statements, indicating more traditional or pessimistic views. Over time, attitudes show modest changes. Among low-FLFP students, disagreement with the statement on employer discrimination becomes more common, yet the share of respondents who strongly agree also increases in both groups. Furthermore, gaps in perceived social judgement appear to widen. Specifically, students from low-FLFP areas become more likely to agree that ambitious women are judged negatively, whereas those from high-FLFP areas display increases at both ends of the scale—greater disagreement, but also a rise in strong agreement.

10.6 Discussion

Overall, these survey findings provide novel insights into potential drivers of *cultural persistence* and plausible mechanisms behind peer effects beyond those previously discussed. A key takeaway is that the broader social environment in which individuals are raised—even beyond family influence—shapes women's beliefs about labor market opportunities and their second-order beliefs regarding gender roles. Women from less gender-

equal areas perceive ambition as less socially acceptable and hold more pessimistic beliefs about their career prospects. While research on belief formation about labor market outcomes is still emerging (Spinnewijn, 2015), these findings suggest that such expectations are shaped early by observing local labor market conditions and may persist even after individuals migrate.[43] Importantly, this highlights the role of information frictions alongside more commonly cited factors—such as attitudes and preferences—in perpetuating norms around female labor market participation. A second key observation concerns the divergent evolution of beliefs. While expectations about job offer arrival rates appear responsive to new information, potentially through peer learning, gaps in perceived gender roles remain more persistent over time. This aligns with prior evidence (e.g., Giavazzi et al., 2019) showing that views on women's societal roles tend to be particularly resistant to change.

11 Conclusions

The persistence of traditional gender roles, reflected in the unequal participation of men and women in paid work, remains a key barrier to gender convergence in the labor market. While many studies have documented the long-run persistence of gender norms, much less attention has been given to understanding the factors that shape their evolution.

This paper provides new evidence that exposure to university classmates born in more gender-equal regions shapes women's labor supply and occupational choices, operating through both changes in job-search preferences and social learning. Italy offers a compelling context for studying cultural norms, given its exceptionally wide geographic variation in gender equality, with female-to-male labor force participation (FLFP) rates ranging from 44% to 86% across provinces. Due to substantial internal mobility, Italian universities bring together students from regions with stark differences in gender equality, who, according to novel data I collected, systematically differ in their labor market expectations and beliefs on gender roles. Because Master's programs are typically small, they exhibit substantial cohort-by-cohort variation in the geographic origins of students, generating quasi-random variation in peer exposure to gender norms that I exploit for identification. I leverage rich administrative data on the peer composition of over 1,500 Master's programs between 2012 and 2016, linked to early-career labor market outcomes and detailed information on students' family backgrounds, education, and job-search preferences.

I find that exposure to female classmates from provinces with higher female labor force participation (FLFP) significantly increases women's likelihood of entering full-time employment, partly through greater sorting into occupations where full-time work is more

[43] Although beyond this paper's scope, the persistence of such beliefs among migrants may also help explain other enduring labor market disparities, such as differences between migrants and natives or between movers from high- versus low-opportunity areas (Chetty and Hendren, 2018).

prevalent. In contrast, men's outcomes remain unaffected, implying that peer exposure can substantially narrow early-career gender gaps—by 21 to 40%, depending on the outcome. Crucially, the effects are not driven by broader regional characteristics: they are robust across a range of gender-specific indicators and fade or disappear when using non-gender-related measures, such as per-capita income or economic activity.

The beneficial impacts of peer exposure are concentrated among women from provinces with below-median FLFP. This asymmetry is striking: a 36 percentage point increase in the share of peers from high-FLFP areas closes up to 65% of the labor supply gap between women from low- and high-FLFP regions, suggesting that peer exposure can partly offset the lasting influence of limited female role models during childhood. These findings imply that policies fostering geographic diversity in higher education could be an effective lever for shifting gender norms and advancing gender equality.

To understand the mechanisms, I combine several new data sources, including a novel survey that I designed to track students' beliefs. Two key channels emerge. First, exposure to peers from more gender-equal regions lowers the value that women place on non-pecuniary job attributes-such as flexibility and leisure- when making career decisions. Second, peer interactions appear to reduce information frictions: women from low-FLFP areas begin their studies with more pessimistic beliefs about their chances of receiving full-time job offers, even when targeting the same labor markets as their high-FLFP peers. These beliefs converge over time, driven by asymmetric updating among women from less gender-equal backgrounds. In contrast, beliefs about traditional gender roles prove more persistent, suggesting that expectations about opportunities are more malleable than deeper cultural attitudes.

Overall, the latter findings point to information frictions as a novel and policy-relevant mechanism behind the persistence of gender norms. Low-cost interventions that improve access to accurate labor market information-particularly for women from more traditional backgrounds- could help shift beliefs and aspirations in ways that meaningfully reduce gender disparities. Further research is needed to identify how such information treatments could replicate the effects of peer-based social learning.

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Tables and Figures

Table I: Summary Statistics: Demographics, Academic Performance and Family Background

	Female			Male			
	Mean	SD	Obs	Mean	SD	Obs	P-value
Individual characteristics							
Age at enrollment	24.3	4.0	182,792	24.5	4.1	133,678	0.00
GPA during Master	27.8	1.5	182,792	27.4	1.7	133,678	0.00
Final grade during Master	108.6	5.6	182,792	107.4	6.3	133,678	0.00
Time to completion of Master (years)	2.5	0.6	182,792	2.6	0.6	133,678	0.00
Bachelor grade	101.3	7.4	162,091	99.1	8.2	116,258	0.00
High school: academic track (%)	84.2	36.5	182,477	71.4	45.2	133,378	0.00
science (%)	40.3	49.0	182,477	56.7	49.5	133,378	0.00
humanities (%)	21.2	40.9	182,477	10.4	30.6	133,378	0.00
foreign language (%)	10.5	30.7	182,477	1.9	13.8	133,378	0.00
social sciences (%)	10.3	30.4	182,477	1.4	11.6	133,378	0.00
arts (%)	1.9	13.7	182,477	1.0	9.8	133,378	0.00
High school: technical track (%)	12.9	33.5	182,477	25.1	43.3	133,378	0.00
High school: vocational track (%)	1.2	10.9	182,477	1.7	12.9	133,378	0.00
International high-school (%)	1.7	12.9	182,477	1.8	13.3	133,378	0.02
High school grade	83.6	11.6	178,593	80.8	12.1	130,134	0.00
Field of study							
Science, chemistry, biology (%)	13.3	34.0	182,792	13.1	33.7	133,678	0.06
Engineering (%)	8.2	27.5	182,792	27.0	44.4	133,678	0.00
Humanities (%)	24.7	43.1	182,792	10.4	30.5	133,678	0.00
Political and social sciences (%)	11.6	32.0	182,792	7.9	26.9	133,678	0.00
Economics and statistics (%)	18.5	38.9	182,792	24.3	42.9	133,678	0.00
Psychology (%)	11.7	32.1	182,792	3.1	17.4	133,678	0.00
Healthcare (%)	4.0	19.7	182,792	2.1	14.4	133,678	0.00
Architecture (%)	3.9	19.5	182,792	4.9	21.6	133,678	0.00
Agriculture (%)	1.9	13.8	182,792	2.9	16.9	133,678	0.00
Family background							
Matched to administrative records	91.7	27.6	182,792	89.6	30.6	133,678	0.00
Mother: university education (%)	18.9	39.2	167,637	22.0	41.4	119,745	0.00
Father: university education (%)	20.0	40.0	167,637	24.0	42.7	119,745	0.00
Mother: high-school education (%)	50.3	50.0	167,637	50.9	50.0	119,745	0.00
Father: high-school education (%)	46.0	49.8	167,637	47.2	49.9	119,745	0.00
Mother is in labor force (%)	71.0	45.4	163,753	73.2	44.3	116,921	0.00
Father is in labor force (%)	99.3	8.0	162,735	99.4	7.5	117,051	0.00
Mother: low SES (%)	59.5	49.1	163,753	55.8	49.7	116,921	0.00
Mother: medium SES (%)	30.2	45.9	163,753	32.6	46.9	116,921	0.00
Mother: high SES (%)	10.4	30.5	163,753	11.6	32.0	116,921	0.00
Father: low SES (%)	45.6	49.8	162,735	40.5	49.1	117,051	0.00
Father: medium SES (%)	23.1	42.1	162,735	24.2	42.8	117,051	0.00
Father: high SES (%)	31.3	46.4	162,735	35.3	47.8	117,051	0.00

Notes. This table reports mean characteristics for female and male students in the sample. Variables are drawn from administrative records and the institutional survey, the latter covering approximately 91% of students. Variation in the number of observations across rows reflects missing information for a subset of students who either did not authorize data use for research purposes or did not respond to specific survey questions. Socioeconomic status (SES) is classified based on parents' occupations into 12 categories.

Table II: Summary Statistics: Labor Market Outcomes and Job-Search Behavior

	Female			Male			
	Mean	SD	Obs	Mean	SD	Obs	P-value
Respond to survey (%)	73.7	44.0	182,792	73.2	44.3	133,678	0.00
Married/cohabiting (%)	16.1	36.8	134,506	9.5	29.3	97,709	0.00
Has children (%)	3.7	18.8	134,514	2.2	14.6	97,724	0.00
Currently employed (%)	53.9	49.8	134,681	61.8	48.6	97,823	0.00
Not currently employed, but has been (%)	15.1	35.8	134,681	11.2	31.6	97,823	0.00
Never employed (%)	31.0	46.3	134,681	27.0	44.4	97,823	0.00
Not currently employed:							
Further education (%)	12.1	32.6	134,479	12.5	33.1	97,663	0.00
Internship/training (%)	12.7	33.3	134,479	9.5	29.3	97,663	0.00
Unemployed searching for a job (%)	16.0	36.7	134,674	12.1	32.7	97,818	0.00
Out of labor force (%)	5.2	22.3	134,674	4.0	19.7	97,818	0.00
Currently employed:							
Net monthly earnings (€)	1,077.8	499.3	69,659	1,324.5	509.6	57,494	0.00
Weekly hours worked	32.9	13.2	69,659	38.6	10.9	57,494	0.00
Full-time job (%)	69.3	46.1	69,659	86.2	34.5	57,494	0.00
Hourly wage	8.9	6.4	69,659	8.9	5.7	57,494	0.67
High earnings occupation (%)	36.7	48.2	68,231	61.5	48.7	56,680	0.00
High full-time occupation (%)	51.3	50.0	68,231	74.5	43.6	56,680	0.00
High earnings industry (%)	34.3	47.5	68,434	48.2	50.0	56,835	0.00
High full-time industry (%)	38.1	48.6	68,434	62.0	48.5	56,835	0.00
Permanent contract (%)	23.0	42.1	69,431	29.4	45.6	57,342	0.00
Fixed-term contract (%)	54.2	49.8	69,431	52.2	50.0	57,342	0.00
Self-employment (%)	16.1	36.8	69,431	15.4	36.1	57,342	0.04
No contract (%)	6.7	25.0	69,431	3.0	17.1	57,342	0.00
Private sector (%)	76.7	42.3	69,570	86.1	34.6	57,450	0.00
Public sector (%)	16.5	37.1	69,570	11.1	31.4	57,450	0.00
No profit (%)	6.9	25.3	69,570	2.8	16.5	57,450	0.00
Use skills acquired during Master (%)	41.8	49.3	69,598	47.3	49.9	57,457	0.00
Job satisfaction (0-10)	7.2	2.0	69,580	7.4	1.7	57,453	0.00
Job-search process							
Job search: months from grad.	0.7	1.8	68,654	0.6	1.5	56,382	0.00
Accept offer: months from grad.	3.0	3.5	69,380	2.7	3.3	57,356	0.00
Number of jobs from grad.	1.3	0.6	69,594	1.2	0.6	57,454	0.00
Current job: first job after grad. (%)	80.3	39.8	69,594	81.0	39.2	57,454	0.00
On-the-job search | part-time (%)	58.0	49.4	21,390	55.9	49.7	7,918	0.00
On-the-job search | full-time (%)	30.8	46.2	48,262	28.8	45.3	49,573	0.00
Received job offer | part-time (%)	19.1	39.3	21,392	19.4	39.5	7,918	0.00
Received job offer | full-time (%)	21.5	41.1	48,267	26.5	44.1	49,576	0.00
Received job offer | unemployed (%)	19.3	39.5	21,589	22.1	41.5	11,870	0.00
Number of job-search channels	3.2	1.8	114,513	3.3	1.8	78443	0.12
Prefer full-time to part-time job (%)	93.6	24.5	165,921	96.1	19.4	118,499	0.00
Available to accept part-time job (%)	82.4	38.1	163,200	61.6	48.6	116,434	0.00

Notes. This table reports mean characteristics for female and male students in the sample. Variables are drawn from the follow-up survey conducted one year after graduation, completed by more than 73% of students. Information on earnings, hours worked and other job characteristics is available only for individuals in standard employment relationships — including those working informally — and excludes individuals in internships or occupation-specific training programs (*praticantato*). Data on preferences for full-time versus part-time employment are drawn from the pre-graduation survey, completed by approximately 91% of students.

Table III: Summary Statistics: Geographical Indicators of Gender Equality

	Mean	SD	Min	Max	Obs
Female labor force participation (age: 15–64)	49.7	11.2	27.3	66.7	316,470
Female/Male labor force participation (age: 15–64)	66.7	11.8	43.0	85.7	316,470
Female labor force participation (age: 25–34)	65.1	15.2	38.0	86.0	316,470
Female/Male labor force participation (age: 25–34)	74.3	13.0	47.0	95.0	316,470
Male labor force participation (age: 15–64)	73.8	4.5	62.9	81.9	316,470
Male labor force participation (age: 25–34)	86.7	6.5	71.4	97.1	316,470
% of female graduates in full-time job	58.3	9.9	39.5	72.3	316,470
% of female/male graduates in full-time job	72.9	7	56.4	82.8	316,470
% of firms without hiring pref. for male workers	54.3	8.9	35.0	71.0	316,470
Historical literacy rates of female/male	81.7	13.1	54.0	100.0	316,470

Notes. The table presents summary statistics for the indicators of local gender equality described in Section 3. The unit of observation is the individual student, assigned to a province based on place of residence prior to Master's enrollment.

Table IV: Geographic Mobility for University Studies, by Gender

	Female		Male		
	Mean (%)	SD	Mean (%)	SD	P-value
Moved to another province for Master	58.9	49.2	55.4	49.7	0.00
Moved to another region for Master	31.3	46.4	29.1	45.4	0.00
Bachelor and Master in same univ.	71.5	45.1	75.7	42.9	0.00
Indicators of gender equality in the province of study					
Female labor force participation (age: 15-64)	52.9	10.5	53.7	10.2	0.00
Female/Male labor force participation (age: 15-64)	70.2	11.3	71.0	11.0	0.00
Female labor force participation (age: 25-34)	69.1	14.2	70.2	13.7	0.00
Female/Male labor force participation (age: 25-34)	78.2	11.9	79.0	11.5	0.00
Male labor force participation (age: 15-64)	74.9	4.0	75.1	3.8	0.00
Male labor force participation (age: 25-34)	87.7	6.1	88.2	5.9	0.00
Female graduates empl. full-time	60.8	9.1	61.8	8.8	0.00
Female/male graduates empl. full-time	74.4	6.4	75.1	6.2	0.00
Firms without hiring pref. for male workers	58.5	8.2	59.1	7.8	0.00

Notes. The table reports summary statistics on students' geographic mobility for graduate studies, by gender. The upper panel presents mobility rates. The lower panel reports indicators of gender equality in the province of study, defined as the province in which students enroll for their Master's degree. All variables are drawn from administrative records and are available for the full sample of 182,792 female and 133,678 male students. P-values correspond to tests of equality of means between female and male students.

Table V: Geographic Mobility into Local Labor Markets, by Gender

	Female			Male			
	Mean (%)	SD	Obs	Mean (%)	SD	Obs	P-value
Work outside province of origin	44.1	49.7	69,548	51.6	50.0	57,417	0.0
Work in province of studies	45.1	49.8	69,548	43.8	49.6	57,417	0.0
Work in region of studies	68.4	46.5	69,548	65.3	47.6	57,417	0.0
Work abroad	5.0	21.7	69,548	5.3	22.3	57,417	0.0
Indicators of gender equality in province of work (excl. abroad)							
Female labor force participation (age 15–64)	54.6	9.7	66,102	55.7	9.2	54,400	0.0
Female/Male labor force participation (age 15–64)	71.8	10.4	66,102	72.9	9.8	54,400	0.0
Female labor force participation (age 25–34)	71.8	13.1	66,102	73.1	12.2	54,400	0.0
Female/Male labor force participation (age 25–34)	79.8	11.0	66,102	80.9	10.2	54,400	0.0
Male labor force participation (age 15–64)	75.7	3.8	66,102	76.0	3.6	54,400	0.0
Male labor force participation (age 25–34)	89.3	5.7	66,102	89.8	5.4	54,400	0.0
Female graduates empl. full-time	62.8	8.7	66,102	63.8	8.3	54,400	0.0
Female/male graduates empl. full-time	76.0	6.2	66,102	76.6	6.0	54,400	0.0
Firms without hiring preference for male workers	58.5	8.3	66,102	59.3	8.0	54,400	0.0

Notes. The table reports summary statistics on students' mobility into local labor markets one year after graduation. In addition to mobility rates by gender, it reports characteristics of the province of employment for individuals employed in Italy (which explains why the sample numerosity falls when zooming in on the characteristics of the province of work). The sample consists of 69,659 female and 57,494 male students who are employed at the time of the follow-up survey, excluding internships and training programs. The smaller sample size reflects missing information on the province of work for a small subset of individuals.

Table VI: Mobility Patterns by FLFP in the Province of Origin (Female Students)

	Q1 FLFP (N=48,896)		**Q4 FLFP** (N=44,103)		
	Mean	SD	Mean	SD	P-value
(1) Moved to another province for Master (%)	57.8	49.4	63.0	48.3	0.00
(2) Moved to another region for Master (%)	37.2	48.3	27.1	44.5	0.00
(3) Work outside province of origin (%)	54.8	49.8	37.8	48.5	0.00
Types of mobility (only for (1))					
FLFP (age: 15-64) in prov. of university	49.7	11.7	60.0	4.4	0.00
Size of university	33797.4	16373.0	36606.5	18288.8	0.00
Nb. of students in the degree	85.2	67.9	86.2	66.1	0.08
% of female students in the degree	58.5	50.5	56.3	46.0	0.00
% of female peers from above-median FLFP provs.	26.7	31.7	67.0	19.7	0.00
% of male peers from above-median FLFP provs.	27.0	32.4	66.8	21.7	0.00
Field of study (only for (1))					
Science, chemistry, biology (%)	13.8	34.5	12.6	33.2	0.00
Engineering (%)	8.3	27.5	6.2	24.2	0.00
Humanities (%)	25.7	43.7	27.1	44.5	0.00
Political and social sciences (%)	11.7	32.2	11.9	32.4	0.45
Economics and statistics (%)	14.2	34.9	17.0	37.6	0.00
Psychology (%)	15.6	36.3	12.3	32.9	0.00
Healthcare (%)	4.3	20.2	3.8	19.1	0.00
Architecture (%)	2.7	16.1	4.8	21.5	0.00
Agriculture (%)	1.4	11.8	2.2	14.6	0.00
Mobility to local labor markets (only for (1))					
FLFP in prov of work	48.5	13.3	61.0	3.5	0.00
Prov. of work = univ. (%)	29.7	45.7	20.0	40.0	0.00
Region of work = univ. (%)	52.4	49.9	63.5	48.1	0.00
Work abroad (%)	5.4	22.7	6.0	23.7	0.10
Work in different prov. than birth (%)	68.8	46.3	45.9	49.8	0.00

Notes. The table reports summary statistics on geographic mobility among female students, comparing individuals originating from provinces in the first versus fourth quartile of FLFP. In addition to overall mobility rates, the table reports characteristics of mobility for the subsample of students who move to another province for their Master's degree.

Table VII: The Gender Earnings Gap At Labor Market Entry

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-time)	(4) Log(Hourly Wage)
Female	-0.113***	-0.083***	-0.051***	-0.029***
	(0.004)	(0.003)	(0.003)	(0.003)
GPA	✓	✓	✓	✓
Degree FEs	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓
Observations	127,153	127,153	127,153	127,153
R-squared	0.294	0.259	0.293	0.088

Notes. The table reports coefficients from regressions of graduates' labor market outcomes on a female indicator, controlling for GPA and including degree and cohort fixed effects. Column (1) reports log net monthly earnings. Column (2) reports log weekly hours worked. Column (3) uses a binary indicator for holding a full-time contract (typically 40 hours per week). Column (4) reports log hourly wages. The sample includes graduates employed under standard contracts (excluding internships and training programs) one year after graduation. Standard errors are clustered at the degree level.

Table VIII: Place-of-Origin Exposure and Women's Labor Supply (Female Movers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Weekly Hours)			Pr(Full-time)		
Born in High- vs. Low-FLFP Province	0.072***	0.076***	0.074***	0.025***	0.022***	0.021***
	(0.011)	(0.011)	(0.011)	(0.008)	(0.008)	(0.008)
Province of job FEs		✓	✓		✓	✓
GPA			✓			✓
Parental background			✓			✓
Degree FEs	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓
Observations	15,838	15,835	15,835	15,838	15,835	15,835
Nb. of degrees	1,218	1,218	1,218	1,218	1,218	1,218
R-squared	0.293	0.302	0.304	0.331	0.348	0.350

Notes. The table reports coefficients from regressions of women's labor market outcomes on an indicator for being born in a province with female labor force participation (FLFP) in the highest versus lowest quartile (equation 1). All regressions include degree and cohort fixed effects. Controls for parental background include fixed effects for parents' educational attainment (10 categories) and occupations (12 categories). The sample consists of female movers, defined as women working in a province different from their province of birth, who are employed one year after graduation. Standard errors are clustered at the degree level.

Table IX: Observable Characteristics of Female Movers by Birth-Province FLFP

	(1) Low FLFP	(2) High FLFP	(3) P-value	(4) Obs
Individual characteristics				
Age at enrollment	23.84	23.83	0.84	16,496
Bachelor grade	101.01	101.84	0.00	14,736
High-school grade	87.58	83.37	0.00	16,123
High school type: academic track (%)	88.78	81.38	0.00	16,463
science (%)	47.64	41.52	0.00	16,463
humanities (%)	23.70	15.16	0.00	16,463
foreign language (%)	9.12	13.15	0.00	16,463
social sciences (%)	7.19	9.66	0.00	16,463
arts (%)	1.13	1.89	0.00	16,463
High school type: technical track (%)	9.89	15.84	0.00	16,463
High school type: vocational track (%)	0.91	0.80	0.54	16,463
Family background				
Mother: university degree (%)	19.03	19.67	0.51	15,185
Father: university degree (%)	19.82	19.58	0.82	15,185
Mother: high-school degree (%)	50.42	52.72	0.03	15,185
Father: high-school degree (%)	47.26	46.25	0.37	15,185
Mother is in the LF (%)	62.24	81.84	0.00	14,866
Father is in the LF (%)	99.36	99.38	0.93	14,766
Mother: low SES (%)	61.15	55.87	0.00	14,866
Mother: medium SES (%)	30.46	32.34	0.08	14,866
Mother: high SES (%)	8.40	11.78	0.00	14,866
Father: low SES (%)	45.62	45.56	0.96	14,766
Father: medium SES (%)	26.22	20.97	0.00	14,766
Father: high SES (%)	28.16	33.47	0.00	14,766

Notes. The table compares observable characteristics of female movers—defined as women working in a province different from their province of birth—by quartile of female labor force participation (FLFP) in the province of birth (top vs. bottom quartile). For each predetermined characteristic, a regression following equation 1 is estimated, including degree and cohort fixed effects. Columns (1) and (2) report predicted values for movers originating from low- and high-FLFP provinces, respectively. Column (3) reports the p-value for the difference between the two groups.

Table X: Place-of-Origin Exposure and Women's Labor Supply (Male Movers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Weekly Hours)			Pr(Full-time)		
Born in High- vs. Low-FLFP Province	0.039***	0.039***	0.038***	0.011*	0.008	0.008
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Province of job FEs		✓	✓		✓	✓
GPA			✓			✓
Parental background			✓			✓
Degree FEs	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓
Observations	15,597	15,595	15,595	15,597	15,595	15,595
Nb. of degrees	1,094	1,094	1,094	1,094	1,094	1,094
R-squared	0.265	0.277	0.279	0.319	0.335	0.337

Notes. The table reports coefficients from regressions of men's labor market outcomes on an indicator for being born in a province with female labor force participation (FLFP) in the highest versus lowest quartile (equation 1). All regressions include degree and cohort fixed effects. Controls for parental background include fixed effects for parents' educational attainment (10 categories) and occupations (12 categories). The sample consists of male movers, defined as men working in a province different from their province of birth, who are employed one year after graduation. Standard errors are clustered at the degree level.

Table XI: Balancedness Of Predicted Labor Market Outcomes

Panel A. Female Sample

	(1) Pr(employed)	(2) Log(monthly earnings)	(3) Log(weekly hours)	(4) Pr(fulltime)
$\hat{\delta}^{FP}$	-0.000	-0.000	-0.001	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)
$\hat{\delta}^{MP}$	-0.000	-0.000	0.002	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	146,476	146,476	146,476	146,476
R-squared	0.119	0.246	0.239	0.273

Panel B. Male Sample

	(1) Pr(employed)	(2) Log(monthly earnings)	(3) Log(weekly hours)	(4) Pr(fulltime)
$\hat{\delta}^{FP}$	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\hat{\delta}^{MP}$	0.001	0.001	0.002	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	106,448	106,448	106,448	106,448
R-squared	0.204	0.259	0.316	0.324

Notes. OLS estimates of a regression of predicted labor market outcomes on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. Regressions include cohort and degree (Master × university) fixed effects and follow the estimating equation 2 in the main text. All regressors are standardized, and standard errors are clustered at the degree level. Labor market outcomes are predicted separately for female and male students using regressions of actual labor market outcomes on predetermined covariates: age, high school type (10 categories), high school grade, Bachelor's grade, dummy variables for mother's and father's citizenship (Italian vs. non-Italian), fixed effects for parents' educational attainment (10 categories), and fixed effects for parents' occupations (12 categories).

Table XII: Raw And Residual Variation Of Peers' Characteristics

	Mean	SD	Min	Max
A: Avg FLFP In Province Of Origin Of Female Peers				
Raw Cohort Variable	49.65	8.50	29.87	66.66
Residuals: Net Of Degree And Cohort FEs	0.00	1.86	-13.80	10.79
B: Avg FLFP In Province Of Origin Of Male Peers				
Raw Cohort Variable	49.72	8.59	27.33	66.66
Residuals: Net Of Degree And Cohort FEs	0.00	2.13	-16.80	14.51

Notes. The table reports descriptive statistics for the average FLFP in the province of origin of female (Panel A) and male (Panel B) students within degrees, before and after removing degree and cohort fixed effects. The unit of observation is a degree-cohort pair, leading to a total of 7,160 observations.

Table XIII: Balancing tests for cohort composition - Female students

Panel A. Educational history and ability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Age	HS science	HS humanities	HS foreign languages	HS social sciences	HS vocational	BSc grade	BSc grade > p50
(Mean)	(24.3)	(0.40)	(0.21)	(0.11)	(0.10)	(0.01)	(101.3)	(0.50)
$\hat{\delta}^{FP}$	-0.030	-0.003	0.002	0.001	0.003	0.002	0.078	-0.001
	(0.092)	(0.006)	(0.005)	(0.004)	(0.004)	(0.001)	(0.124)	(0.008)
$\hat{\delta}^{MP}$	-0.110	-0.009*	-0.000	0.002	-0.004	0.001	-0.009	-0.001
	(0.095)	(0.005)	(0.004)	(0.003)	(0.004)	(0.001)	(0.090)	(0.006)
Degree FEs	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	182,792	182,792	182,792	182,792	182,792	182,792	162,091	162,091
R-squared	0.168	0.139	0.107	0.125	0.128	0.020	0.204	0.149

Panel B. Parental background

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mother: univ.	Father: univ.	Mother: HS	Father: HS	Mother: low SES	Mother: high SES	Father: low SES	Father: high SES
(Mean)	(0.19)	(0.20)	(0.50)	(0.46)	(0.59)	(0.10)	(0.46)	(0.31)
$\hat{\delta}^{FP}$	-0.002	-0.009	0.007	-0.005	-0.009	-0.004	0.007	-0.007
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)
$\hat{\delta}^{MP}$	-0.004	-0.006	-0.001	0.006	0.007	-0.002	0.008	0.001
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
Degree FEs	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	167,637	167,637	167,637	167,637	163,753	163,753	162,735	162,735
R-squared	0.043	0.042	0.019	0.015	0.039	0.026	0.036	0.038

Notes. The table reports OLS estimates of $\hat{\delta}^{FP}$ and $\hat{\delta}^{MP}$ from equation 2. Each column corresponds to a separate regression where the dependent variable is a pre-determined covariate: educational history and ability (Panel A) or parental background (Panel B). Regressions include cohort and degree fixed effects. Means are shown in parentheses. The sample includes all female students (N = 182,792). Sample sizes vary due to missing covariates from institutional surveys. Regressors are standardized; dependent variables are not. Standard errors clustered at the degree level.

Table XIV: Balancing tests for cohort composition – Male students

Panel A. Educational history and ability

	(1) Age	(2) HS science	(3) HS humanities	(4) HS foreign languages	(5) HS social sciences	(6) HS vocational	(7) BSc grade	(8) BSc grade > p50
(Mean)	(24.5)	(0.57)	(0.10)	(0.02)	(0.01)	(0.02)	(99.1)	(0.50)
$\hat{\delta}^{FP}$	0.045	0.010	-0.006	0.000	-0.001	0.000	0.239*	0.017**
	(0.059)	(0.006)	(0.004)	(0.002)	(0.001)	(0.002)	(0.129)	(0.008)
$\hat{\delta}^{MP}$	-0.070	-0.003	0.004	-0.002	0.003	-0.000	-0.136	-0.005
	(0.074)	(0.007)	(0.005)	(0.002)	(0.002)	(0.002)	(0.124)	(0.008)
Degree FEs	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	133,678	133,678	133,678	133,678	133,678	133,678	116,258	116,258
R-squared	0.218	0.106	0.121	0.070	0.055	0.044	0.234	0.173

Panel B. Parental background

	(1) Mother: univ.	(2) Father: univ.	(3) Mother: HS	(4) Father: HS	(5) Mother: med SES	(6) Mother: high SES	(7) Father: med SES	(8) Father: high SES
(Mean)	(0.22)	(0.24)	(0.51)	(0.47)	(0.33)	(0.12)	(0.24)	(0.35)
$\hat{\delta}^{FP}$	-0.000	-0.012**	-0.012*	0.005	-0.001	-0.000	0.009	-0.007
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)
$\hat{\delta}^{MP}$	-0.005	-0.001	0.000	0.004	-0.004	-0.004	-0.015**	0.014*
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)
Degree FEs	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	119,745	119,745	119,745	119,745	116,921	116,921	117,051	117,051
R-squared	0.037	0.036	0.020	0.019	0.038	0.030	0.033	0.041

Notes. The table reports OLS estimates of $\hat{\delta}^{FP}$ and $\hat{\delta}^{MP}$ from equation 2. Each column corresponds to a different regression, where the dependent variables are pre-determined covariates of a student, related to educational history and ability (Panel A), and parental background (Panel B). Regressions include cohort and degree fixed effects. Below each variable name, sample means are shown in parentheses. The sample consists of all male students in the sample (N=133,678). Variations in sample sizes across columns arise from missing information on some of the covariates. All regressors are standardised. Standard errors are clustered at the degree level.

Tables: Main Results

Table XV: Peer Effects On Earnings And Labor Supply, Female Sample

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(hourly wage)
$\hat{\delta}^{FP}$	0.037***	0.033***	0.019**	0.004
	(0.013)	(0.012)	(0.009)	(0.012)
$\hat{\delta}^{MP}$	0.000	0.001	-0.001	-0.001
	(0.010)	(0.010)	(0.007)	(0.010)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.288	0.246	0.280	0.099

Notes. OLS estimates of equation 2, regressing women's earnings and hours worked one year after graduation on the average FLFP in the provinces of origin of female and male peers. All specifications control for the share of female and male international students in the program-cohort cell, the FLFP in the student's own province of origin, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XVI: Peer Effects On Earnings And Labor Supply, Male Sample

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(hourly wage)
$\hat{\delta}^{FP}$	0.012	-0.002	-0.001	0.013
	(0.008)	(0.008)	(0.006)	(0.008)
$\hat{\delta}^{MP}$	0.013	-0.005	0.004	0.018*
	(0.011)	(0.010)	(0.008)	(0.010)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	57,476	57,476	57,476	57,476
R-squared	0.246	0.233	0.270	0.105

Notes. OLS estimates of equation 2, regressing men's earnings and hours worked one year after graduation on the average FLFP in the provinces of origin of female and male peers. All specifications control for the share of female and male international students in the program-cohort cell, the FLFP in the student's own province of origin, as well as cohort and degree fixed effects. The sample is restricted to Italian-born men employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XVII: Peer Effects On Survey Response And Labor Market Participation

	(1) Pr(Survey response)	(2) Pr(Missing salary)	(3) Pr(Work in first year)	(4) Pr(Employed now)
Panel A. Female Sample				
$\hat{\delta}^{FP}$	-0.005	0.002	0.002	0.002
	(0.006)	(0.004)	(0.007)	(0.008)
$\hat{\delta}^{MP}$	-0.005	0.001	-0.003	-0.010*
	(0.005)	(0.003)	(0.006)	(0.006)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	182,792	72,584	134,680	134,680
R-squared	0.052	0.027	0.114	0.129
Panel B. Male Sample				
$\hat{\delta}^{FP}$	0.007	-0.001	-0.005	0.003
	(0.006)	(0.004)	(0.007)	(0.008)
$\hat{\delta}^{MP}$	-0.004	0.000	-0.006	-0.002
	(0.006)	(0.005)	(0.007)	(0.008)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	133,678	60,440	97,823	97,823
R-squared	0.057	0.037	0.112	0.141

Notes. OLS estimates of equation 2, regressing survey response and labor market participation outcomes on the average FLFP in the provinces of origin of female and male peers. All specifications control for the share of female and male international students in the program-cohort cell, the FLFP in the student's own province of origin, as well as cohort and degree fixed effects. The sample is restricted to Italian-born students with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XVIII: Peer Effects on Occupations and Industries, Female Sample

	(1)	(2)	(3)	(4)	(5)
	Occupation		Industry		Log(weekly hours)
	High earn.	High full-time	High earn.	High full-time	
$\hat{\delta}^{FP}$	0.017**	0.016*	0.014	0.007	0.022**
	(0.009)	(0.009)	(0.010)	(0.009)	(0.011)
$\hat{\delta}^{MP}$	-0.004	-0.005	-0.003	-0.009	-0.001
	(0.006)	(0.006)	(0.007)	(0.006)	(0.009)
Job type FE					✓
Degree FE	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓
Observations	68,216	68,216	68,419	68,419	69,645
R-squared	0.361	0.466	0.272	0.398	0.369

Notes. OLS estimates of equation 2, regressing occupational and industry outcomes one year after graduation on the average FLFP in the provinces of origin of female and male peers. The dependent variables in Columns (1) and (3) are binary indicators for whether a graduate works in an occupation or industry with above-median earnings, respectively. Those in Columns (2) and (4) are binary indicators for whether the occupation or industry has an above-median share of full-time employment. Column (5) re-estimates the effect on log weekly hours adding occupation fixed effects (20 classes) and industry fixed effects (21 classes), to assess the extent to which occupational sorting accounts for the labor supply effects. All specifications control for the share of female and male international students in the program-cohort cell, the FLFP in the student's own province of origin, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XIX: Peer Effects on Sector and Job Stability, Female Sample

	(1) Permanent	(2) No Contract	(3) Self-Employed	(4) Public Sector	(5) Non-Profit
δ^{FP}	-0.002	-0.007	-0.003	0.001	0.007
	(0.010)	(0.005)	(0.008)	(0.009)	(0.005)
δ^{MP}	-0.008	-0.004	-0.012*	0.001	0.003
	(0.007)	(0.004)	(0.007)	(0.008)	(0.005)
Degree FE	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓
Observations	69,417	69,417	69,417	69,556	69,556
R-squared	0.137	0.098	0.144	0.203	0.153

Notes. OLS estimates of equation 2, regressing job contract type and sector one year after graduation on the average FLFP in the provinces of origin of female and male peers. All dependent variables are binary indicators. All specifications control for the share of female and male international students in the program-cohort cell, the FLFP in the student's own province of origin, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XX: Sensitivity to Indicators of Gender Equality in Peers' Provinces - Peer Effects on Earnings and Labor Supply, Female Sample - Alternative Indicators of Gender Equality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: log(monthly earnings)							
	Measures of peers' gender culture							
	FLFP	FLFP (young)	FLFP/MLFP	FLFP/MLFP (young)	% of female grad. full-time	female/male grad. full-time	Firms' culture	F/M Literacy
$\hat{\pi}^{FP}$	0.037***	0.041***	0.034***	0.036***	0.041***	0.044***	0.017**	0.030***
	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.008)	(0.011)
$\hat{\pi}^{MP}$	0.000	0.003	0.001	0.003	0.010	0.001	0.004	0.013
	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)	(0.010)	(0.006)	(0.009)
Degree FE	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645	69,645	69,645	69,645	69,645
R-squared	0.288	0.288	0.287	0.287	0.288	0.288	0.287	0.287

Notes. OLS estimates of equation 3, using alternative indicators of gender equality in peers' provinces of origin in place of the baseline FLFP measure. The dependent variable is log monthly earnings in all columns. Each column corresponds to a separate regression using a different gender equality indicator, as labeled. All specifications control for the share of female and male international students in the program-cohort cell, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Tables: Robustness

Table XXI: Peer Effects on Female Outcomes: Robustness to Degree-Specific Time Trends

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-Time)	(4) Log(Hourly Wage)
$\hat{\delta}^{FP}$	0.045***	0.039***	0.029***	0.006
	(0.014)	(0.014)	(0.010)	(0.014)
$\hat{\delta}^{MP}$	-0.001	-0.009	-0.004	0.008
	(0.011)	(0.011)	(0.008)	(0.011)
Degree FE	✓	✓	✓	✓
Degree Trends	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.308	0.266	0.299	0.124

Notes. OLS estimates of equation 2, augmented to include degree-specific linear time trends. The trends are constructed as a within-degree sequence variable — taking values 0, 1, 2, 3, 4 across enrollment cohorts — and interacted with degree fixed effects, thereby allowing each program to follow its own linear trajectory in outcomes over time. All specifications control for the share of female and male international students in the program-cohort cell, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XXII: Peer Effects on Female Outcomes: Robustness to Region-of-Study Time Trends

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-Time)	(4) Log(Hourly Wage)
$\hat{\delta}^{FP}$	0.035***	0.030**	0.019**	0.006
	(0.013)	(0.012)	(0.009)	(0.012)
$\hat{\delta}^{MP}$	-0.001	-0.001	-0.002	-0.000
	(0.010)	(0.009)	(0.007)	(0.009)
Degree FE	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.288	0.246	0.281	0.100

Notes. OLS estimates of equation 2, augmented to include region-of-study-specific linear time trends. The trends are constructed as a within-region sequence variable — taking values 0, 1, 2, 3, 4 across enrollment cohorts — and interacted with region-of-study fixed effects, thereby allowing each region to follow its own linear trajectory in outcomes over time. This specification controls for the possibility that smooth changes in local labor market conditions or student composition at the regional level confound the peer effect estimates. The peer effect estimates remain stable and statistically significant, consistent with the baseline results. All specifications control for the share of female and male international students in the program-cohort cell, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XXIII: Estimates of Peer Effects on Female Earnings – Excluding Degrees with Trends in Size

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-Time)	(4) Log(Hourly Wage)
$\hat{\delta}^{FP}$	0.052***	0.029*	0.030***	0.023
	(0.015)	(0.015)	(0.011)	(0.014)
$\hat{\delta}^{MP}$	0.003	-0.004	-0.003	0.007
	(0.012)	(0.012)	(0.008)	(0.010)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	45,643	45,643	45,643	45,643
R-squared	0.285	0.250	0.280	0.093

Notes. OLS estimates of equation 2, regressing women's earnings and hours worked one year after graduation on the average FLFP in the provinces of origin of female and male peers. All specifications control for the share of female and male international students in the program-cohort cell, the FLFP in the student's own province of origin, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. It excludes programs in which cohort size exhibits a statistically significant linear time trend at the 10% level. All regressors are standardized.

Table XXIV: Estimates of Peer Effects on Female Earnings – Excluding Degrees with Trends in Avg. FLFP

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-Time)	(4) Log(Hourly Wage)
$\hat{\delta}^{FP}$	0.051***	0.042***	0.029***	0.010
	(0.014)	(0.014)	(0.010)	(0.013)
$\hat{\delta}^{MP}$	0.011	0.000	0.000	0.001
	(0.011)	(0.011)	(0.008)	(0.010)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	50,204	50,204	50,204	50,204
R-squared	0.276	0.237	0.270	0.094

Notes. OLS estimates of equation 2, regressing women's earnings and hours worked one year after graduation on the average FLFP in the provinces of origin of female and male peers. All specifications control for the share of female and male international students in the program-cohort cell, the FLFP in the student's own province of origin, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. It excludes programs in which the average FLFP of students' provinces of origin exhibits a statistically significant linear time trend at the 10% level. Standard errors are clustered at the degree level. All regressors are standardized.

Table XXV: Estimates of Peer Effects on Female Earnings, Excluding Degrees with Large Shocks to Composition

	(1) Benchmark	(2) Δ size<=p75	(3) Δ size<=p50	(4) Δ avg grades<=p75	(5) Δ avg grades<=p25	(6) Δ sd grades<=p75	(7) Δ sd grades<=p25
$\hat{\delta}^{FP}$	0.037***	0.049***	0.052***	0.037**	0.043*	0.036**	0.053**
	(0.013)	(0.013)	(0.015)	(0.015)	(0.025)	(0.014)	(0.022)
$\hat{\delta}^{MP}$	0.000	-0.001	-0.001	-0.003	-0.003	0.002	-0.004
	(0.010)	(0.011)	(0.013)	(0.011)	(0.014)	(0.012)	(0.014)
Degree FE	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓
Nb. of degrees	1,572	1,163	770	1,170	390	1,171	389
Observations	69,645	58,363	42,518	59,040	25,564	60,613	28,741
R-squared	0.288	0.294	0.309	0.280	0.251	0.278	0.284

Notes. The table reports estimates from equation 2. The dependent variable is log(monthly earnings) in all columns. Regressions include cohort and degree fixed effects. The Table analyzes the sensitivity of estimates across different subsamples of degrees. Column (1) and (2) are based on a sample of degrees with cross-cohort changes in size below the 75th and 50th percentiles (definitions in Subsection 7.1). Column (3) and (4) are based on a sample of degrees with cross-cohort changes in average students' ability below the 75th or 25th percentile. Column (5) and (6) are based on a sample of degrees with cross-cohort changes in the sd of students' ability below the 75th or 25th percentile. The estimates are done on the sample of women, studying in these degrees, who are employed one year after graduation and with non-missing information on the dependent variables. Standard errors clustered at degree level. All regressors are standardised.

Table XXVI: Peer Effects on Female Earnings: Sensitivity to Sample Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Degree size					Students with Bsc in same uni		Share intern. students	
	Benchmark	>p10	<=p90	<=mean	>mean	>p90	<=p90	<=p25	=0	<=p90
$\hat{\delta}^{FP}$	0.037***	0.030**	0.039***	0.048***	0.021	0.016	0.037***	0.048**	0.055***	0.039***
	(0.013)	(0.013)	(0.014)	(0.016)	(0.020)	(0.028)	(0.013)	(0.019)	(0.023)	(0.013)
$\hat{\delta}^{MP}$	0.000	-0.000	-0.003	-0.008	0.009	0.012	0.001	0.008	-0.008	-0.003
	(0.010)	(0.010)	(0.012)	(0.012)	(0.016)	(0.018)	(0.010)	(0.012)	(0.019)	(0.011)
Degree FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	69,645	68,438	46,641	23,050	46,595	23,004	65,453	21,886	28,120	64,904
R-squared	0.288	0.287	0.266	0.256	0.300	0.329	0.284	0.254	0.304	0.285

Notes. OLS estimates of equation 2 on log monthly earnings across alternative sample restrictions. Column (1) replicates the baseline estimate on the full sample. Columns (2)–(6) restrict the sample by average program size (average across cohorts): Column (2) excludes programs with an average cohort size below 13 students (bottom decile); Column (3) excludes programs with an average size above 87 students (top decile); Column (4) restricts to programs with an average size below 43 students (below mean); Column (5) restricts to programs with an average size above 43 students (above mean);

Column (6) restricts to programs with an average size above 87 students (top decile). Columns (7)–(8) restrict the sample by the share of students who completed their Bachelor's at the same institution: Column (7) excludes programs where more than 96% of students share the same undergraduate institution; Column (8) excludes programs where more than 61% of students share the same undergraduate institution. Columns (9)–(10) restrict the sample by the share of international students: Column (9) focuses on programs with no international students; Column (10) focuses on programs where fewer than 12.5% of students are international. All specifications (except for Columns (9)–(10)) control for the share of female and male international students in the program-cohort cell, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XXVII: Peer Effects on Female Earnings: Robustness to Alternative Peer Characteristics

	Dependent variable: log(monthly earnings)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\hat{\delta}^{FP}$	0.038***	0.039***	0.039***	0.039***	0.039***	0.039***	0.039***	0.044***	0.036***	0.037***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)
$\hat{\delta}^{MP}$	0.001	0.002	0.002	0.002	0.002	0.001	-0.001	0.002	-0.000	-0.000
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share of peers with work. mother	✓									
Share of peers with high-SES mother		✓								
Share of peers with high-SES father			✓							
Share of peers with college educ mother				✓						
Share of peers with college educ father					✓					
Share of high-ability peers						✓				
Share of peers from academic track							✓			
Share of peers with BSc at same univ.								✓		
Degree size									✓	
Share of female peers										✓
Degree FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	69,487	69,487	69,519	69,534	69,534	69,487	69,645	69,523	69,645	69,645
R-squared	0.289	0.289	0.289	0.289	0.289	0.290	0.288	0.289	0.288	0.288

Notes. OLS estimates of equation 2, augmented to include controls for alternative individual-level characteristics of peers, disaggregated by gender. Each column adds a different peer-level control: share of peers with a working mother (Column 1), share with a high-SES mother (Column 2), share with a high-SES father (Column 3), share with a college-educated mother (Column 4), share with a college-educated father (Column 5), share of high-ability peers — defined as those with an above-median Bachelor's grade — (Column 6), share of peers from academic-track high schools (Column 7), share of peers who completed their Bachelor's at the same institution (Column 8), cohort size (Column 9), and share of female peers (Column 10). Estimates are stable across all columns, indicating that the baseline peer effect is not confounded by differences in socioeconomic background, academic ability, or cohort composition between students from high- and low-FLFP provinces. Most peer characteristics are constructed from the institutional survey. In these specifications, regressions additionally control for the share of female and male peers who completed the survey. The sample size is slightly reduced in some columns because students enrolled in programs where no peer completed the survey — a pattern concentrated in very small programs — are excluded by construction. All specifications control for the share of female and male international students in the program-cohort cell, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XXVIII: Peer Effects on Female Earnings: Robustness to Geographical Controls

	Dependent variable: log(monthly earnings)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\hat{\delta}^{FP}$	0.034**	0.034***	0.037**	0.042***	0.036***	0.032	0.041***
	(0.015)	(0.013)	(0.013)	(0.013)	(0.012)	(0.023)	(0.015)
$\hat{\delta}^{MP}$	-0.004	-0.002	-0.001	-0.001	0.003	-0.001	0.006
	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)	(0.017)	(0.012)
Per capita income in munic of female peers	✓						
Per capita income in munic of male peers	✓						
Size of munic of female peers		✓					
Size of munic of male peers		✓					
Female peers from urban areas			✓				
Male peers from urban areas			✓				
Service sector in prov of female peers				✓			
Service sector in prov of male peers				✓			
Fertility rate in prov of female peers					✓		
Fertility rate in prov of male peers					✓		
MLFP in prov of female peers						✓	
MLFP in prov of male peers						✓	
Female education in prov of female peers							✓
Female education in prov of male peers							✓
Degree FE	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645	69,645	69,645	69,645
R-squared	0.288	0.288	0.288	0.288	0.288	0.288	0.288

Notes. OLS estimates of equation 2, augmented to include controls for alternative geographical characteristics of peers' provinces of origin. Each column corresponds to a separate regression adding a different set of controls: per capita income (Column 1), municipality size (Column 2), share of peers from urban areas (Column 3), share of firms in the service sector (Column 4), fertility rate (Column 5), male labor force participation (Column 6), and the share of women aged 19–34 with a high-school diploma (Column 7). The stability of the estimates across specifications indicates that the baseline peer effects do not reflect broader geographical characteristics of peers' provinces. All specifications control for the share of female and male international students in the program-cohort cell, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XXIX: Placebo Tests: Alternative Characteristics of Peers' Provinces

	Dependent variable: log(monthly earnings)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Per capita income in munic. of female peers	0.013*						
	(0.007)						
Per capita income in munic. of male peers	0.004						
	(0.005)						
Size of munic. of female peers		0.013					
		(0.009)					
Size of munic. of male peers		0.007					
		(0.007)					
Female peers from urban areas			0.001				
			(0.004)				
Male peers from urban areas			0.005				
			(0.004)				
Service sector in prov of female peers				0.009			
				(0.010)			
Service sector in prov of male peers				-0.005			
				(0.008)			
Fertility rate in prov of female peers					-0.006		
					(0.010)		
Fertility rate in prov of male peers					0.008		
					(0.008)		
MLFP in prov of female peers						0.032***	
						(0.013)	
MLFP in prov of male peers						0.001	
						(0.010)	
Female education in prov of female peers							0.016
							(0.011)
Female education in prov of male peers							-0.003
							(0.009)
Degree FE	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645	69,645	69,645	69,645
R-squared	0.287	0.287	0.287	0.287	0.287	0.287	0.287

Notes. OLS estimates of equation 2, replacing the baseline FLFP peer measure with non-gender-specific characteristics of peers' provinces (or municipalities) of origin. Each column corresponds to a separate placebo regression: per capita income (Column 1), municipality size (Column 2), share of peers from urban areas (Column 3), share of firms in the service sector (Column 4), fertility rate (Column 5), male labor force participation (Column 6), and share of women aged 19–34 with a high-school diploma (Column 7). If the baseline peer effects were driven by broader geographical characteristics rather than gender-specific cultural environments, we would expect significant coefficients in these regressions. The absence of significant effects across specifications — with the partial exception of MLFP, which is closely correlated with FLFP — supports the gender-cultural interpretation of the baseline results. All specifications control for the share of female and male international students in the program-cohort cell, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table XXX: Peer Effects and Childhood-Environment Gaps

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)
$\hat{\beta}_2$	0.024***	0.037***	0.005
	(0.008)	(0.008)	(0.006)
$\hat{\gamma}_2$	0.013	0.005	0.003
	(0.008)	(0.008)	(0.007)
$\hat{\beta}_3$	0.059***	0.058***	0.030***
	(0.013)	(0.012)	(0.010)
$\hat{\gamma}_3$	-0.035***	-0.038***	-0.030***
	(0.013)	(0.012)	(0.010)
$\hat{\beta}_4$	0.060***	0.060***	0.023***
	(0.010)	(0.011)	(0.008)
$\hat{\gamma}_4$	-0.018	-0.035***	-0.024**
	(0.012)	(0.012)	(0.010)

Notes. The table reports selected estimates from equation (5). The coefficients $\widehat{\beta}_q$ capture the average outcome difference between women in FLFP quartile q and women in the omitted first quartile, evaluated at the mean share of female peers from above-median-FLFP provinces. The coefficients $\widehat{\gamma}_q$ capture the difference between the peer effect for women in quartile q and the corresponding effect for women in the first quartile. The peer-share variables are standardized to have mean zero and standard deviation one. The FLFP-quartile indicators are not standardized. All specifications control for the share of male peers from above-median-FLFP provinces and include degree and cohort fixed effects. Standard errors, clustered at the degree level, are reported in parentheses.

Table XXXI: Estimates of Peer Effects on Academic Performance and Migration Choices

	Panel A. Academic performance				Panel B. Migration			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GPA	Final grade	Time to completion	Pr(delayed grad.)	FLFP in prov. of work	Prov work = univ.	Reg work = univ.	Prov of work ≠ birth
(Mean)	(27.8)	(108.6)	(2.5)	(0.35)	(54.6)	(0.45)	(0.68)	(0.44)
δ^{FP}	0.047	0.071	-0.004	-0.007	0.155	0.007	0.013	0.007
	(0.029)	(0.102)	(0.010)	(0.008)	(0.151)	(0.011)	(0.011)	(0.010)
δ^{MP}	0.039	0.066	-0.006	-0.005	0.126	-0.010	-0.005	0.009
	(0.024)	(0.085)	(0.008)	(0.007)	(0.123)	(0.008)	(0.008)	(0.007)
Degree FE	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	182,792	182,792	182,792	182,792	66,102	66,102	66,102	66,102
R-squared	0.244	0.174	0.161	0.148	0.586	0.156	0.152	0.181

Notes. OLS estimates of a regression of indicators of academic performance on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. Regressions include cohort and degree fixed effects. In Panel A, the dependent variables are: contemporaneous GPA (Column 1), final grade (Column 2), time to completion (Column 3), probability of delayed graduation (Column 4). In Panel B, the dependent variables are: FLFP in the province of employment (Column 5), an indicator of whether the province of employment is the same as that of the university attended (Column 6), an indicator of whether the region of employment matches the university's region (Column 7), and an indicator of whether the province of employment differs from the province of birth (Column 8). All the estimates are done on the full sample of women. All regressors are standardised. All regressors are standardised, while the dependent variables are not. The mean values of the dependent variables are provided in the table. Standard errors clustered at degree level.

Table XXXII: Estimates of Peer Effects on Female Earnings and Labor Supply Controlling for Share of Local Students

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(hourly wage)
δ^{FP}	0.045***	0.041***	0.022**	0.003
	(0.013)	(0.012)	(0.010)	(0.013)
δ^{MP}	-0.002	-0.002	-0.001	-0.000
	(0.010)	(0.010)	(0.007)	(0.010)
Share of female stayers	-0.011*	-0.010*	-0.004	-0.000
	(0.006)	(0.006)	(0.004)	(0.005)
Share of male stayers	0.003	0.006	-0.001	-0.003
	(0.005)	(0.005)	(0.004)	(0.004)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.288	0.246	0.280	0.100

Notes. OLS estimates of a regression of women's earnings and labor supply one year after graduation on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin, as well as the share of *local* female and male peers. A student is defined as *local* if she studies at university in her province of birth. Regressions include cohort and degree fixed effects. All the estimates are done on the sample of women employed one year post-graduation, with non-missing data on the relevant variables. Standard errors clustered at degree level. All regressors are standardised.

Table XXXIII: Estimates of Peer Effects on Job-Search Preferences

	(1) Index Pecuniary	(2) Index Flexibility	(3) Job's social utility
δ^{FP}	0.003	-0.027*	-0.012*
	(0.009)	(0.015)	(0.007)
δ^{MP}	0.001	0.006	0.001
	(0.007)	(0.011)	(0.005)
Degree FE	✓	✓	✓
Cohort FE	✓	✓	✓
Observations	165,116	163,855	164,214
R-squared	0.089	0.043	0.093

Notes. OLS estimates of regressions of valuation of job attributes on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. The dependent variables in Columns (1)-(3) measure the importance students place on different job characteristics. Answers come from the question: "How much do you value attribute X in the job you are searching?" (scale 1-5). Specifically, Column (1) reflects preferences for pecuniary job attributes, i.e., salary and career progression, based on a standardized index constructed from students' rankings on a 1-5 scale. The index in Column (2) is constructed by averaging students' rankings of job attributes related to flexibility (i.e., leisure time and hours flexibility). Both indexes in (1) and (2) have been standardised. The dependent variable in Column (3) is an indicator variable for whether a student gives maximum value to the social utility of a job. Regressions include cohort and degree fixed effects. The estimates are done on the sample of women who fill in the institutional pre-graduation survey (91.7%). Standard errors clustered at degree level. All regressors are standardised.

Table XXXIV: Main Characteristics of Female Students in the New Data Collection

	All			Low FLFP		High FLFP	
	Mean	SD	N	Mean	SD	Mean	SD
Background Characteristics							
Age	23.4	1.8	487	23.6	2.3	23.3	1.5
Changed province for Master (%)	88.8	31.6	490	100.0	0.0	82.6	37.9
Changed region for Master (%)	69.6	46.0	490	100.0	0.0	53.0	50.0
FLFP in province of origin	54.6	11.2	489	41.9	8.9	61.5	4.0
Mother: university level (%)	31.4	46.5	468	27.3	44.7	33.7	47.3
Father: university level (%)	28.0	44.9	465	32.7	47.1	25.3	43.6
Mother: full-time at childbirth (%)	49.9	50.1	465	45.7	50.0	52.2	50.0
Mother: part-time at childbirth (%)	30.1	45.9	465	23.2	42.3	33.9	47.4
Mother: no work at childbirth (%)	20.0	40.0	465	31.1	46.4	14.0	34.7
Field of study							
Major: Economics (%)	19.2	39.4	480	20.0	40.1	18.7	39.1
Major: Humanities (%)	45.2	49.8	480	40.0	49.1	48.1	50.0
Major: Science (%)	20.4	40.4	480	23.5	42.5	18.7	39.1
Major: Social Sciences (%)	15.2	35.9	480	16.5	37.2	14.5	35.3
First year (%)	65.1	47.7	490	61.8	48.7	66.9	47.1
Second year (%)	33.5	47.2	490	38.2	48.7	30.9	46.3
Above second year (%)	1.4	11.9	490	0.0	0.0	2.2	14.7
Civil Status and Fertility Expectations							
Single (%)	48.1	50.0	468	46.1	50.0	49.2	50.1
Has a partner (%)	46.4	49.9	468	48.5	50.1	45.2	49.9
Cohabits with partner (%)	5.6	22.9	468	5.5	22.8	5.6	23.1
Partner in same program (%)	3.4	18.2	468	2.4	15.4	4.0	19.5
Intend to have children (%)	54.0	49.9	470	52.7	50.1	54.8	49.9
Maybe children (%)	33.2	47.1	470	35.8	48.1	31.8	46.6
Does not intend to have children (%)	12.6	33.2	470	11.5	32.0	13.1	33.8
Has children already (%)	0.2	4.6	470	0.0	0.0	0.3	5.7
Expected age at first child	31.3	2.8	351	31.7	3.2	31.1	2.6
Intended Job Search							
Intend to search for a job (%)	79.7	40.3	488	80.8	39.5	79.1	40.7
Intend to pursue further education (%)	19.1	39.3	488	18.0	38.6	19.6	39.8
Intend to keep job (%)	1.2	11.0	488	1.2	10.8	1.3	11.2
Job location: North (%)	61.2	48.8	485	62.2	48.6	60.7	48.9
Job location: Centre (%)	15.7	36.4	485	14.0	34.8	16.6	37.3
Job location: South (%)	2.7	16.2	485	7.0	25.5	0.3	5.7
Job location: Abroad (%)	20.4	40.3	485	16.9	37.5	22.4	41.7

Notes. This table summarizes the main characteristics of the sample of prospective female students that participated in the data collection at the University of Bologna. It reports the mean and standard deviation of variables related to students' background, fields of study, civil status, partner information, fertility expectations, and labor market intentions. Statistics are shown for the overall sample (490 students), as well as for subsamples from above-median (317 students) and below-median (173 students) FLFP provinces.

Table XXXV: Baseline and Updated Beliefs on the Job Offer Distribution

	Below-med FLFP		**Above-med FLFP**		
	Pred	SE	Pred	SE	P-value
a. Baseline Beliefs (T=0)					
α: Expected arrival rate of job offers (%)	32.06	1.77	35.24	1.24	0.15
γ: Expected % of part-time job offers	57.64	2.29	51.19	1.61	0.02
Prob. to accept part-time job offer	67.43	2.04	60.39	1.44	0.01
b. Updated Beliefs (T=1)					
α: Expected arrival rate of job offers (%)	32.20	2.17	32.19	1.73	1.00
γ: Expected % of part-time job offers	52.47	2.90	50.70	2.31	0.64
Prob. to accept part-time job offer	62.48	2.81	62.37	2.23	0.98

Notes. This table presents predictions from a linear regression model, where the dependent variable is regressed on an indicator for whether the FLFP in the birth province is above or below the median, along with fixed effects for the field of study. Each row represents a different regression, with the dependent variable specified in Column 1. The last column provides the p-value for the difference between the two groups. In Panel (a), the sample consists of all first-year female Master's students (319), and in Panel (b), it includes all second-year female Master's students (164). Between 60% and 65% of the students in the two cohorts are from provinces with above-median FLFP.

Table XXXVI: Baseline and Updated Expectations of Fertility and Future Labor Supply

	Below-med FLFP		Above-med FLFP		
	Pred	SE	Pred	SE	P-value
a. Baseline Expectations (T=0)					
Fertility: yes	0.50	0.05	0.54	0.04	0.50
Fertility: don't know	0.38	0.05	0.35	0.03	0.61
Fertility: no	0.12	0.03	0.11	0.02	0.76
Age of expected fertility	31.58	0.31	30.88	0.23	0.07
Labor supply at motherhood (Scenario 1)					
Work full-time	0.49	0.05	0.43	0.04	0.40
Work part-time	0.49	0.05	0.55	0.04	0.38
No work	0.03	0.02	0.03	0.02	0.90
Labor supply at motherhood (Scenario 2)					
Work full-time	0.70	0.05	0.68	0.04	0.81
Work part-time	0.28	0.05	0.31	0.04	0.58
No work	0.03	0.02	0.01	0.01	0.21
b. Updated Expectations (T=1)					
Fertility: yes	0.57	0.07	0.61	0.05	0.63
Fertility: don't know	0.32	0.06	0.23	0.04	0.27
Fertility: no	0.10	0.04	0.15	0.04	0.41
Age of expected fertility	32.65	0.44	31.13	0.35	**0.01**
Labor supply at motherhood (Scenario 1)					
Work full-time	0.67	0.06	0.41	0.06	**0.00**
Work part-time	0.33	0.06	0.55	0.06	**0.02**
No work	0.04	0.03			
Labor supply at motherhood (Scenario 2)					
Work full-time	0.79	0.05	0.80	0.05	0.85
Work part-time	0.21	0.05	0.20	0.05	0.85
No work	0.00		0.00		

Notes. This table presents predictions from logistic regressions, where the dependent variable is regressed on an indicator for whether the FLFP in the birth province is above or below the median, along with fixed effects for the field of study. Each row represents a different regression, with the dependent variable specified in Column 1. For each regression, the table reports the predicted dependent variable for women from provinces with low versus high FLFP, along with the standard errors. The last column provides the p-value for the difference between these two groups. In Panel (a), the sample consists of all first-year female Master's students without missing information on the dependent variables, and in Panel (b), it includes all second-year female Master's students without missing information on the dependent variables. Between 60% and 65% of the students are from provinces with above-median FLFP.

Table XXXVII: Baseline and Updated Attitudes

	Below-med FLFP		**Above-med FLFP**		
	Pred	SE	Pred	SE	P-value
Baseline Beliefs (T=0)					
Employers' discrimination					
Strongly disagree	0.03	0.02	0.02	0.01	0.55
Disagree	0.04	0.02	0.15	0.03	0.00
Agree	0.65	0.05	0.56	0.04	0.12
Strongly agree	0.27	0.05	0.26	0.03	0.78
Ambition is negatively judged					
Strongly disagree	0.08	0.03	0.04	0.01	0.23
Disagree	0.21	0.04	0.28	0.03	0.21
Agree	0.42	0.05	0.46	0.04	0.54
Strongly agree	0.28	0.04	0.21	0.03	0.16
Updated Beliefs (T=1)					
Employers' discrimination					
Strongly disagree					
Disagree	0.13	0.05	0.12	0.03	0.87
Agree	0.50	0.07	0.57	0.05	0.41
Strongly agree	0.36	0.06	0.31	0.05	0.57
Ambition is negatively judged					
Strongly disagree	0.03	0.02	0.05	0.02	0.49
Disagree	0.14	0.05	0.25	0.05	0.12
Agree	0.48	0.07	0.41	0.05	0.43
Strongly agree	0.35	0.07	0.28	0.05	0.42

Notes. This table presents predictions from a linear probability model, where the dependent variable (agreement with one of the statements) is regressed on an indicator for whether the FLFP in the birth province is above or below the median, along with fixed effects for the field of study. Each row represents a different regression, with the dependent variable specified in Column 1. The statements to which students should express agreement with are "Employers prefer to hire men for full-time positions" and "A woman is negatively judged if she is too ambitious". In the upper panel, the sample comprises all first-year female Master's students without missing information on the dependent variables, and in the lower panel, it includes all second-year female Master's students without missing information on the dependent variables. Between 60% and 65% of the students in the two cohorts are from provinces with above-median FLFP.

Table XXXVIII: Baseline and Updated Beliefs on the Job Offer Distribution - Robustness

	Below-med FLFP		Above-med FLFP		
	Pred	SE	Pred	SE	P-value
a. Baseline Beliefs (T=0)					
α: Expected arrival rate of job offers (%)	32.30	1.80	35.05	1.26	0.23
γ_P: Expected % of part-time job offers	57.48	2.43	50.33	1.70	0.02
Perceived uncertainty (1-5)	2.80	0.13	2.93	0.09	0.44
Prob. to accept part-time job offer	67.26	2.17	59.66	1.50	0.01
b. Updated Beliefs (T=1)					
α: Expected arrival rate of job offers (%)	32.82	2.47	32.43	1.93	0.91
γ_P: Expected % of part-time job offers	52.41	3.11	51.89	2.43	0.90
Perceived uncertainty (1-5)	2.63	0.15	2.74	0.12	0.57
Prob. to accept part-time job offer	62.03	2.94	63.94	2.28	0.63

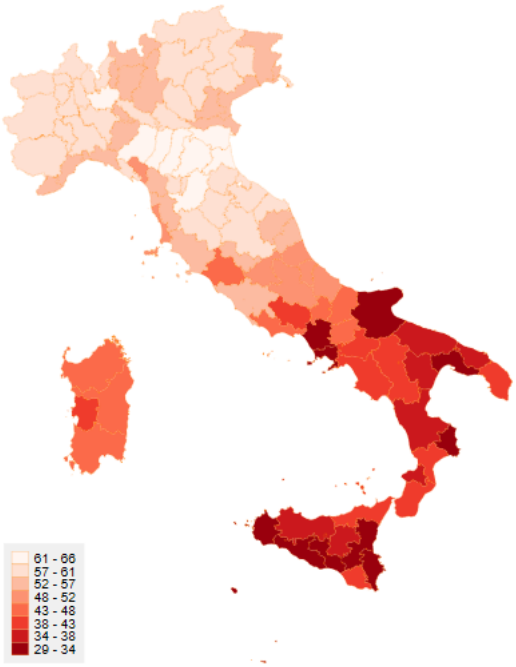
Notes. This table presents predictions from a linear regression model, where the dependent variable is regressed on an indicator for whether the FLFP in the birth province is above or below the median, along with fixed effects for the field of study and controls for students' background characteristics (age, parents' education), job search intentions, and expected job location. Each row represents a different regression, with the dependent variable specified in Column 1. For each regression, the table reports the predicted dependent variable for women from provinces with low versus high FLFP, along with the standard errors. The last column provides the p-value for the difference between these two groups. In Panel (a), the sample consists of all first-year female Master's students without missing information on the covariates (291), and in Panel (b), it includes all second-year female Master's students without missing information on the covariates (148). Between 60% and 65% of the students are from provinces with above-median FLFP.

Table XXXIX: Acceptance of Part-time Jobs and Expectations on Job Offer Arrival Rates

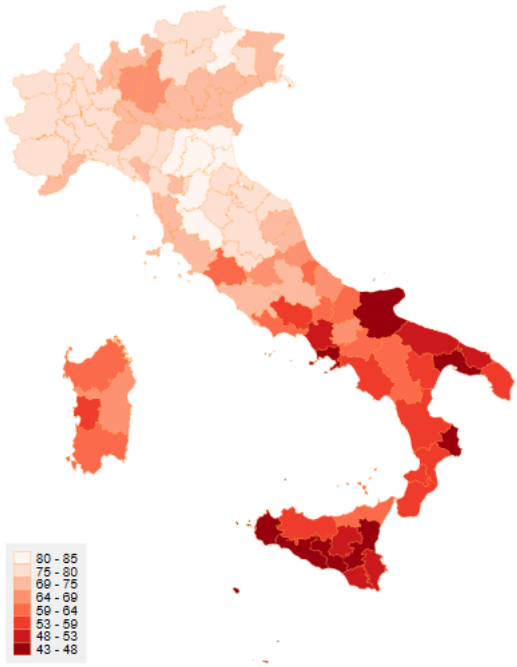
	(1)	(2)	(3)	(4)
	Probability to accept part-time job offer			
Expected percentage of part-time offers (γ)	0.327**	0.272**		
	(0.066)	(0.056)		
Expected arrival rate of job offers (α)			-0.148**	-0.078
			(0.028)	(0.035)
Field FEs		✓		✓
Observations	463	463	464	464
R-squared	0.125	0.171	0.014	0.101

The table presents estimates from linear regressions of the likelihood of accepting a part-time job offer (intented) on workers' expected probability of receiving a job offer (Columns 1-2) or the expected percentage of part-time offers (Columns 3-4). In Columns 2 and 4, I include controls for the field of study. The sample consists of all female students with non-missing values for these variables, drawn from both the first and second year of the program.

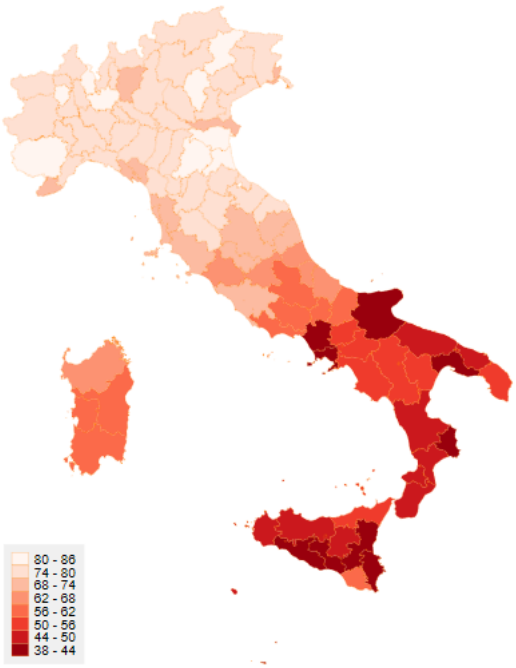
Figure I: Geographical Variation in Gender Equality Indicators



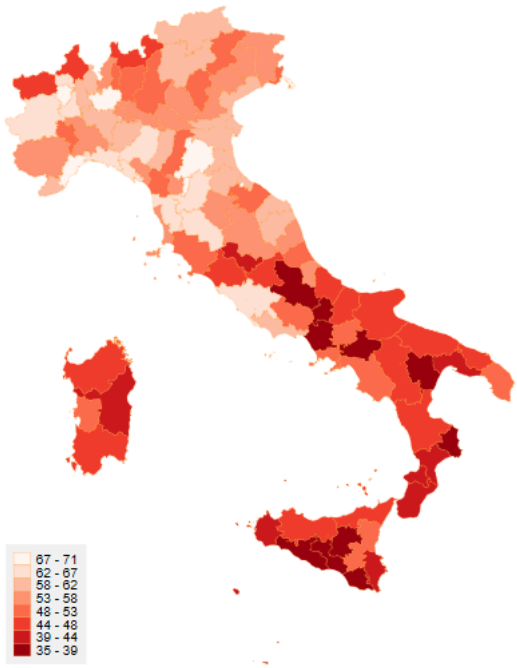
(a) FLFP (%) - Age: 15-64



(b) FLFP/MLFP (%) - Age: 15-64



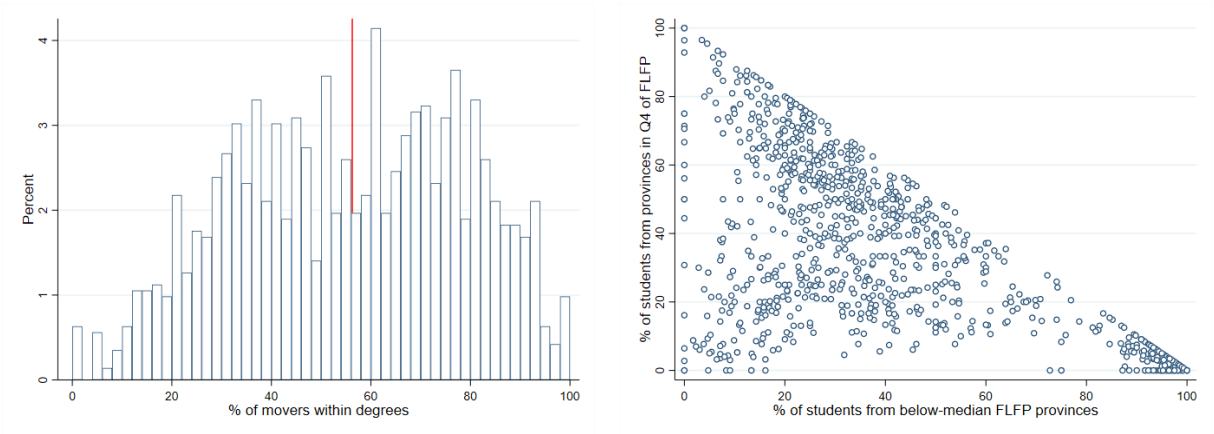
(c) FLFP (%) - Age: 25-34



(d) % of firms without preference for male workers

Notes. These figures depict the geographical distribution of gender equality indicators across Italian provinces. Panels (a) and (b) show female labor force participation (FLFP) and the FLFP-to-MLFP ratio for women aged 15–64. Panel (c) reports FLFP among younger women aged 25–34. All three indicators are computed as averages over the period 2004–2007. Panel (d) displays the share of firms reporting no hiring preference for male workers in 2003.

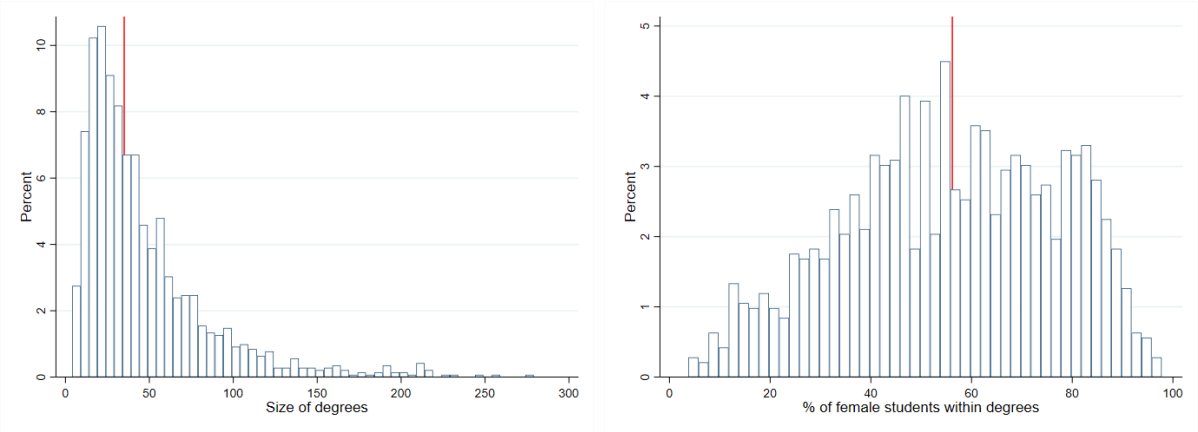
Figure II: Student Mobility and Geographical Composition of Master's Programs



(a) Mobility **(b)** Geographical origins

Notes. Each observation corresponds to a degree program (N=1,572). Panel (A) plots programs by the share of students who moved outside their birth province to enroll; the red line indicates the median. Panel (B) plots programs by the share of students originating from provinces in the top quartile of FLFP (y-axis) against the share from the bottom two quartiles (x-axis). Data refer to 2016.

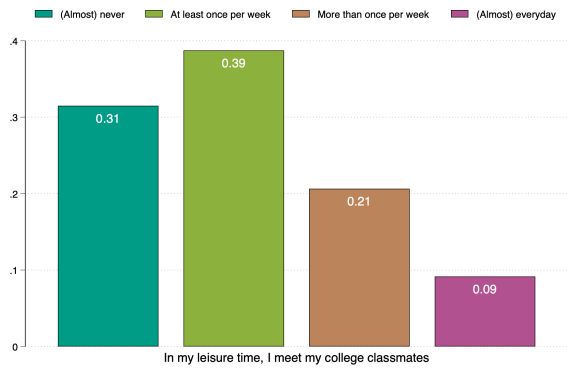
Figure III: Size and Gender Composition of Master's Programs



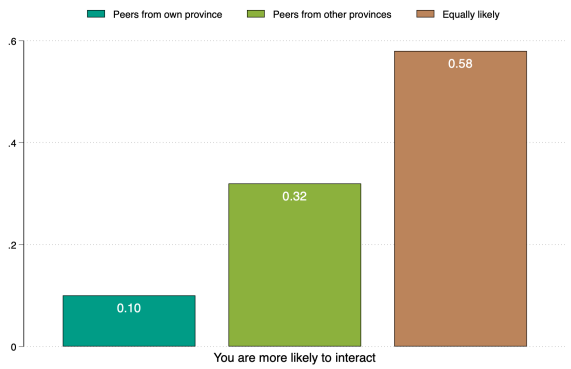
(a) Size **(b)** % of female students

Panel (A) shows the distribution of programs by number of enrolled students; Panel (B) by the share of female students. Red vertical lines indicate the median of each distribution. Data refer to 2016.

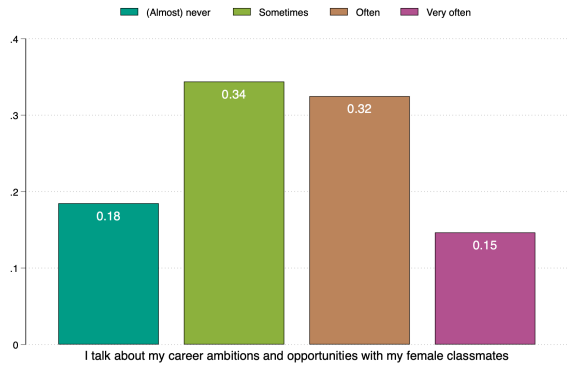
Figure IV: Social Interactions During the Master's Program



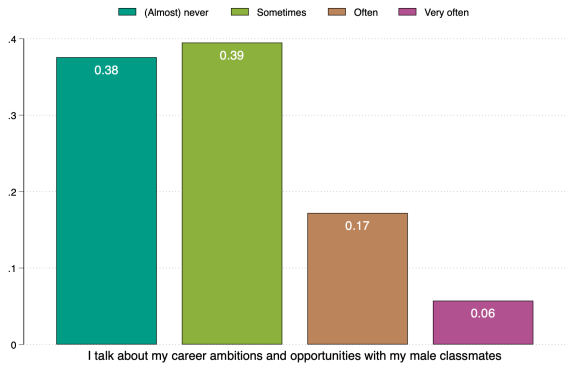
(a) Frequency



(b) Network structure



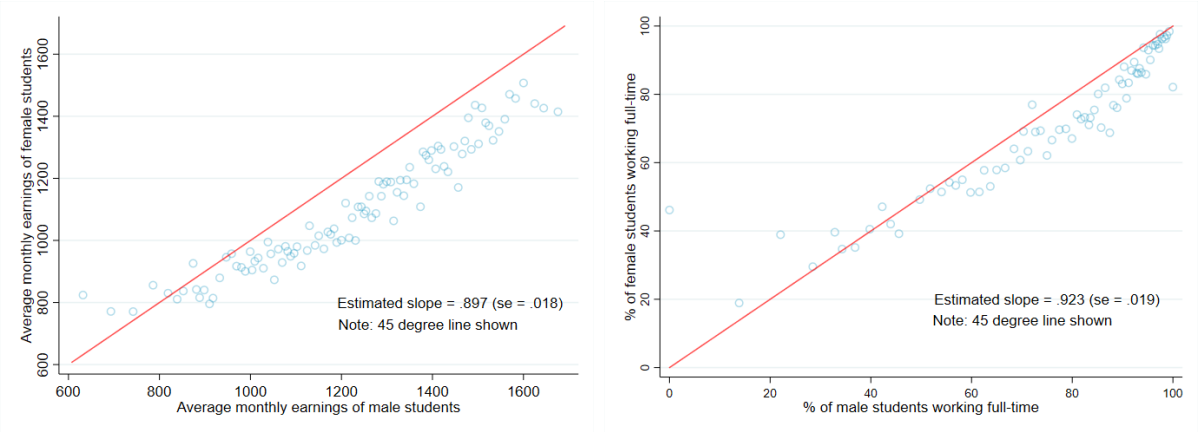
(c) Career opportunities



(d) Career opportunities

Notes. This figure reports responses from female students to an original survey conducted across multiple fields at the University of Bologna ($N = 490$). Panels (A) and (B) pool responses from first- and second-year students, as network structure does not differ meaningfully across cohorts. Panels (C) and (D) display responses from students at the beginning of their second year ($N = 171$), since students are substantially less likely to discuss career opportunities at the start of the first year. Survey questions are reported on the horizontal axes.

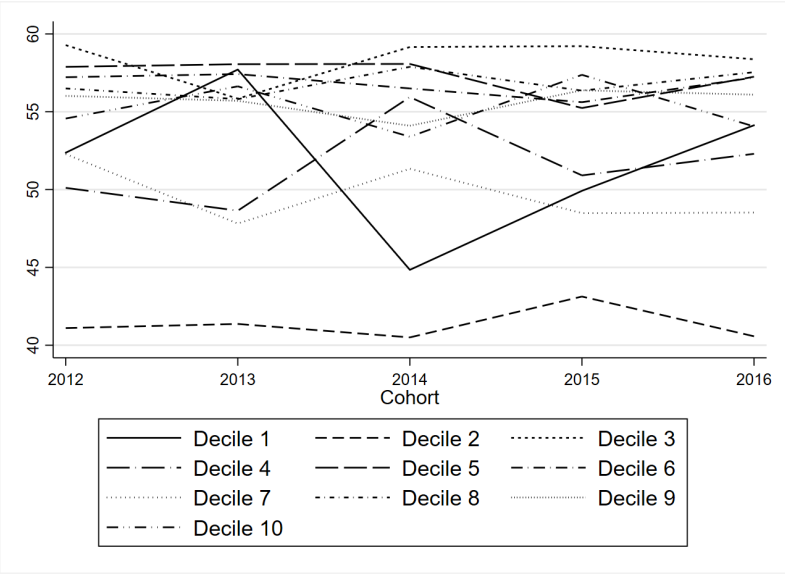
Figure V: Gender-Specific Degree Effects on Earnings and Labor Supply at Entry



(a) Net monthly earnings **(b)** Full-time employment

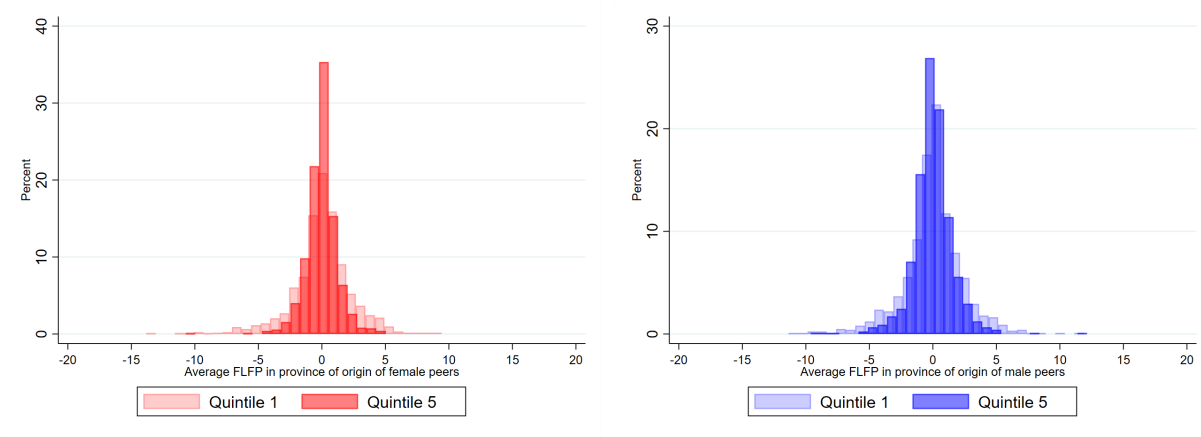
Notes. The figure displays binned scatter plots of estimated degree-level effects for female students against estimated degree-level effects for male students. Each degree is characterized by the average earnings (Panel A) or full-time employment rate (Panel B) of male students (x-axis) and female students (y-axis), computed across all years. The slope is estimated by OLS across degrees, weighting each degree by its share of students. Each observation corresponds to a degree program. The red line denotes the 45-degree line.

Figure VI: Time-Series Evolution of Students' Geographic Origins within Randomly Selected Degree Programs



Notes. This figure shows the time-series evolution of the average female labor force participation (FLFP) in the province of origin of female peers within ten randomly selected degree programs. Programs are first grouped into deciles based on their average cohort size across all years, and one program is randomly drawn from each decile.

Figure VII: Year-to-Year Variation in Students' Geographical Origins by Program Size

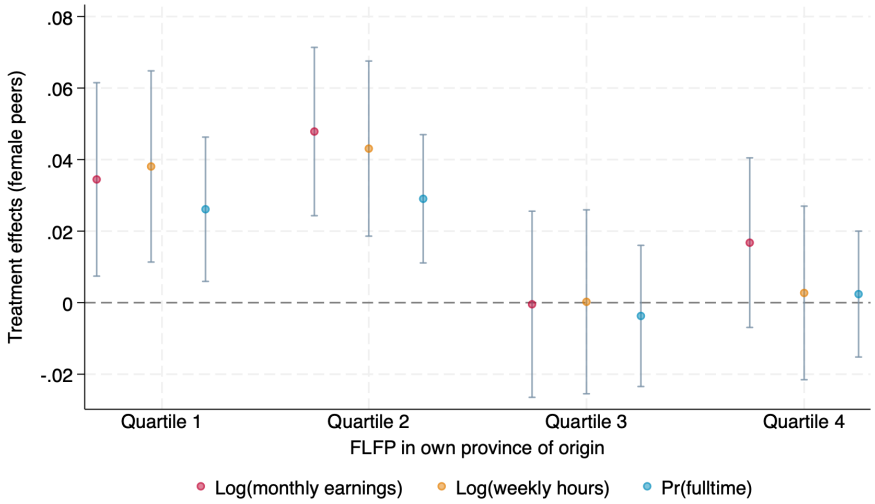


(a) Female peers

(b) Male peers

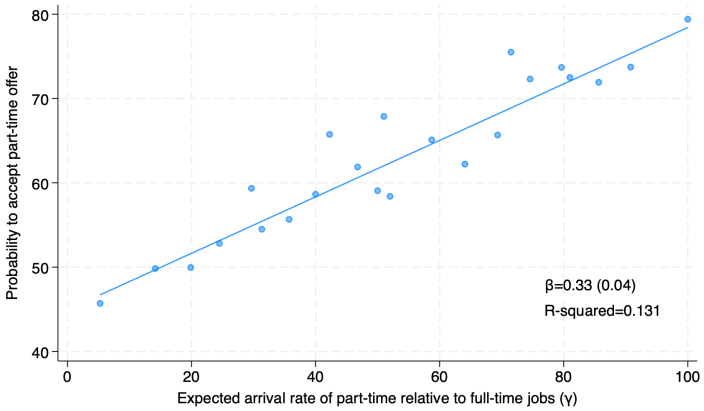
Notes. The figure plots the distribution of residuals from a OLS regression of the average FLFP in the province of origin of female (Panel a) or male students (Panel b) on cohort and degree fixed effects. The distributions are shown separately for degree programs in the first and highest quintiles of size. Degree programs are divided into quintiles based on their average size across five cohorts: the first quintile includes degrees with fewer than 22 students, while the fifth quintile includes degrees with 70 to 410 students. Each observation represents a degree-cohort pair. Histograms are presented by bins of 0.75.

Figure VIII: Peer Effects by Students' Own Childhood Environment



Notes. The figure reports the estimated effect of a one-standard-deviation increase in the share of female peers from provinces with above-median FLFP, separately by the FLFP quartile of the student's province of origin. The outcomes are log monthly earnings, log weekly hours, and an indicator for full-time employment. The estimates are obtained from equation 5, in which the share of female peers from above-median-FLFP provinces is interacted with indicators for the student's own FLFP quartile. The specification also controls for the corresponding share of male peers and includes degree and cohort fixed effects. Standard errors are clustered at the degree level.

Figure IX: Acceptance of part-time jobs and expected share of part-time job offers



Notes. This figure presents binned scatter plots of the probability of accepting a part-time job against the expected arrival rate of part-time relative to full-time job offers (γ). One observation represents a student in the sample. β is the estimated coefficient from a simple linear regression of the intended probability of accepting a part-time offer on the expected share of part-time job offers.

Appendix

Appendix A: Additional Tables

Table A.I: Summary Statistics of Geographical Indicators of Gender Equality, by Gender

	Female		**Male**		
	Mean	SD	Mean	SD	P-value
Female labor force participation (age: 15-64)	49.3	11.2	50.2	11.1	0.00
Female/Male labor force participation (age: 15-64)	66.3	11.9	67.2	11.8	0.00
Female labor force participation (age: 25-34)	64.6	15.3	65.8	15.1	0.00
Female/Male labor force participation (age: 25-34)	73.9	13.1	74.9	12.9	0.00
Male labor force participation (age: 15-64)	73.7	4.6	74.0	4.5	0.00
Male labor force participation (age: 25-34)	86.5	6.5	87.0	6.4	0.00
% of female graduates in full-time job	56.0	9.6	56.8	9.5	0.00
% of female/male graduates in full-time job	71.6	6.7	72.1	6.6	0.00
% of firms without hiring pref. for male workers	34.5	7.8	35.1	7.8	0.00
Historical literacy rates of female/male	81.3	13.2	82.2	12.9	0.00

Notes. The table presents summary statistics of the geographical indicators of gender equality (1–6) discussed in Section 3, broken down by students' gender. The sample includes 182,792 female and 133,678 male students. Students are assigned to provinces based on their province of residence prior to enrollment in the Master's program. The similarity in these statistics across genders indicates that, on average, students' geographical origins do not differ by gender.

Table A.II: Summary Statistics of Non–Gender-Specific Geographical Characteristics

Variable	Mean	SD	Min	Max	Obs
% of firms in service sector	75.2	5.2	58.7	83.3	316,470
% of women with high-school educ.	58.4	6.7	46.8	71.4	316,470
Fertility rate	39.6	3.8	29.6	47.4	316,470
Per capita income (municipality)	19062.4	4146.8	7330.5	46566.6	316,470
Number of taxpayers (municipality)	193214.4	465215.8	29.0	1869353.0	316,470
Childcare availability	18.5	5.1	7.0	33.0	316,470

Notes. The table reports summary statistics for additional, non–gender-specific geographical characteristics. The unit of observation is the student. Students are assigned to provinces or municipalities based on their place of residence prior to enrollment in the Master's program. All measures are defined at the province level unless otherwise noted.

Table A.III: Pairwise Correlations Between FLFP and Other Geographical Indicators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) FLFP	1.000										
(2) FLFP/MFLP	0.989	1.000									
(3) MLFP	0.905	0.836	1.000								
(4) Firm's culture	0.723	0.711	0.654	1.000							
(5) % of firms in service sector	-0.426	-0.381	-0.499	0.071	1.000						
(6) % of women (19-34) with high-school diploma	0.645	0.694	0.445	0.581	0.120	1.000					
(7) Fertility rate	-0.291	-0.355	-0.118	-0.008	0.203	-0.452	1.000				
(8) Per capita income	0.795	0.764	0.761	0.798	-0.213	0.410	0.036	1.000			
(9) SD of per capita income	0.167	0.174	0.108	0.372	0.199	0.131	0.133	0.426	1.000		
(10) Historical literacy rates of female vs. male	0.508	0.448	0.591	0.589	-0.173	-0.041	0.266	0.793	0.368	1.000	
(11) Childcare availability	0.662	0.662	0.554	0.642	0.017	0.645	-0.176	0.574	0.119	0.282	1.000

Notes. The table reports pairwise correlations between female labor force participation measures and other geographical indicators in the sample. The unit of observation is the student, who is assigned to a province based on place of residence prior to enrollment in the Master's program. All variables are defined at the province level.

Table A.IV: Mobility Patterns by FLFP in the Province of Origin (Male Students)

	Q1 FLFP (N=32,575)		**Q4 FLFP** (N=34,298)		
	Mean	SD	Mean	SD	P-value
(1) Moved to another province for Master (%)	54.7	49.8	60.1	49.0	0.00
(2) Moved to another region for Master (%)	37.1	48.3	23.8	42.6	0.00
(3) Work outside province of origin (%)	66.0	47.4	44.5	49.7	0.00
Types of mobility (only for (1))					
FLFP (age: 15-64) in prov. of university	51.0	11.7	60.1	4.4	0.00
Size of university	32890.6	16138.3	36319.7	17790.2	0.00
Nb. of students in the degree	90.0	79.3	86.2	72.3	0.00
% of female students in the degree	39.4	38.8	39.0	38.8	0.27
% of female peers from above-median FLFP provs.	32.0	32.9	68.6	21.2	0.00
% of male peers from above-median FLFP provs.	32.5	32.6	68.9	20.3	0.00
Field of study (only for (1))					
Science, chemistry, biology (%)	10.8	31.0	15.8	36.5	0.00
Engineering (%)	29.1	45.4	22.7	41.9	0.00
Humanities (%)	10.0	30.0	12.4	33.0	0.00
Political and social sciences (%)	9.0	28.6	7.4	26.1	0.00
Economics and statistics (%)	22.3	41.6	22.4	41.7	0.83
Psychology (%)	3.9	19.4	3.7	19.0	0.36
Healthcare (%)	2.7	16.1	2.0	14.0	0.00
Architecture (%)	3.8	19.0	5.6	23.0	0.00
Agriculture (%)	2.6	15.9	3.7	18.9	0.00
Mobility to local labor markets (only for (1))					
FLFP in prov of work	51.5	12.6	60.9	3.6	0.00
Prov. of work = univ. (%)	32.8	46.9	21.4	41.0	0.00
Region of work = univ. (%)	51.4	50.0	62.3	48.5	0.00
Work abroad (%)	5.9	23.5	6.0	23.7	0.74
Work in different prov. than birth (%)	78.6	41.0	53.3	49.9	0.00

Notes. The table reports summary statistics on geographic mobility among male students, comparing individuals originating from provinces in the first versus fourth quartile of FLFP. In addition to overall mobility rates, the table reports characteristics of mobility for the subsample of students who move to another province for their Master's degree.

Table A.V: Summary Statistics of Master's Program Characteristics

	Mean	SD	p50	Min	Max
Size of degree	48.0	43.9	35.0	4.0	410.0
% of female students	55.6	21.3	56.2	3.8	97.1
% of students from above-median FLFP provs.	40.8	36.3	50.0	0.0	100.0
% of international students	2.3	6.0	0.0	0.0	55.0
% of students with BSc at same univ.	72.9	22.6	78.4	0.0	100.0
Nb. of distinct provinces within a program	13.9	12.0	10.0	1.0	81.0
% of isolated students	21.2	16.9	18.2	0.0	100.0
Avg. nb. of peers from own prov. of origin	11.7	16.0	7.0	0.0	296.5
% of isolated students (high-school)	72.5	19.4	73.8	15.2	100
Avg. nb. of peers from same high-school	0.5	0.7	0.3	0.0	8.7

Notes. The table reports summary statistics for key characteristics of Master's programs, averaged over the period 2012–2016. The unit of observation is the degree program, with 1,572 programs included in the sample.

Table A.VI: Gender Differences in Labor Market Participation at Entry

	(1) Out of Labor Force	(2) Has Any Contract in LM	(3) Standard Employment	(4) Internship
Female	-0.001	0.002	-0.012***	0.015***
	(0.001)	(0.002)	(0.003)	(0.001)
GPA	✓	✓	✓	✓
Degree FEs	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓
Observations	232,492	232,504	232,504	232,142
R-squared	0.023	0.117	0.128	0.080

Notes. The table reports coefficients from regressions of graduates' labor market participation one year after graduation on a female indicator, controlling for GPA and including degree and cohort fixed effects. Column (1) indicates whether a student is out of the labor force. Column (2) indicates whether a student holds any employment contract at the time of the survey. Column (3) indicates employment under a standard contract (excluding internships and training programs). Column (4) indicates employment under an internship contract. All specifications are estimated by OLS. Standard errors are clustered at the degree level.

Table A.VII: The Gender Earnings Gap At Labor Market Entry

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-time)	(4) Log(Hourly Wage)
Female	-0.087***	-0.057***	-0.032***	-0.030***
	(0.003)	(0.003)	(0.002)	(0.003)
GPA	✓	✓	✓	✓
Job characteristics	✓	✓	✓	✓
Degree FEs	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓
Observations	127,153	127,153	127,153	127,153
R-squared	0.294	0.259	0.293	0.088

Notes. The table reports coefficients from regressions of graduates' labor market outcomes on a female indicator, controlling for GPA and including degree and cohort fixed effects, as well as controls for job location, occupation and industry FEs. Column (1) reports log net monthly earnings. Column (2) reports log weekly hours worked. Column (3) uses a binary indicator for holding a full-time contract (typically 40 hours per week). Column (4) reports log hourly wages. The sample includes graduates employed under standard contracts (excluding internships and training programs) one year after graduation. Standard errors are clustered at the degree level.

Table A.VIII: The Gender Gap at Labor Market Entry: Excluding Married Individuals and Parents

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-time)	(4) Log(Hourly Wage)
Female	-0.107***	-0.080***	-0.046***	-0.027***
	(0.004)	(0.004)	(0.003)	(0.003)
GPA	✓	✓	✓	✓
Degree FEs	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓
Observations	106,360	106,360	106,360	106,360
R-squared	0.314	0.269	0.300	0.092

Notes. The table reports coefficients from regressions of graduates' labor market outcomes on a female indicator, controlling for GPA and including degree and cohort fixed effects. The sample includes female and male students employed one year after graduation, excluding individuals who are married or cohabiting and those with children. Standard errors are clustered at the degree level.

Table A.IX: Observable Characteristics of Male Movers by Birth-Province FLFP

	(1) Low FLFP	(2) High FLFP	(3) P-value	(4) Obs
Individual characteristics				
Age at enrollment	24.01	23.89	0.03	16,294
Bachelor grade	98.72	98.76	0.88	14,319
High-school grade	84.54	80.51	0.00	15,846
High school type: academic track (%)	75.16	67.87	0.00	16,260
science (%)	63.35	57.82	0.00	16,260
humanities (%)	9.53	5.90	0.00	16,260
foreign language (%)	1.35	1.82	0.11	16,260
social sciences (%)	0.51	1.50	0.00	16,260
arts (%)	0.41	0.83	0.00	16,260
High school type: technical track (%)	23.39	28.44	0.00	16,260
High school type: vocational track (%)	1.28	1.50	0.42	16,260
Family background				
Mother: university degree (%)	21.59	22.19	0.58	14,635
Father: university degree (%)	22.28	24.52	0.05	14,635
Mother: high-school degree (%)	50.15	53.44	0.01	14,635
Father: high-school degree (%)	48.15	47.70	0.74	14,635
Mother is in the LF (%)	62.75	81.30	0.00	14,315
Father is in the LF (%)	99.40	99.53	0.52	14,350
Mother: low SES (%)	58.42	54.64	0.00	14,315
Mother: medium SES (%)	32.85	33.76	0.37	14,315
Mother: high SES (%)	8.73	11.60	0.00	14,315
Father: low SES (%)	41.83	38.48	0.01	14,350
Father: medium SES (%)	27.77	21.80	0.00	14,350
Father: high SES (%)	30.40	39.73	0.00	14,350

Notes. The table compares observable characteristics of female movers—defined as women working in a province different from their province of birth—by quartile of female labor force participation (FLFP) in the province of birth (top vs. bottom quartile). For each predetermined characteristic, a regression following equation 1 is estimated, including degree and cohort fixed effects. Columns (1) and (2) report predicted values for movers originating from low- and high-FLFP provinces, respectively. Column (3) reports the p-value for the difference between the two groups.

Table A.X: Raw and Residual Variation of Peers' Measures by Quintiles of Degree Size

	Mean	SD	Min	Max
A: Avg FLFP in province of origin of female peers				
Quintile 1 (<18 students)				
Raw cohort variable	48.84	8.86	29.87	66.66
Residuals: net of degree and cohort FEs	-0.00	2.24	-13.79	8.95
Quintile 2 (18–27 students)				
Raw cohort variable	50.07	8.33	31.14	66.18
Residuals: net of degree and cohort FEs	0.00	2.05	-9.83	8.51
Quintile 3 (27–40 students)				
Raw cohort variable	50.14	8.25	29.89	66.65
Residuals: net of degree and cohort FEs	0.00	1.99	-12.93	8.29
Quintile 4 (40–64 students)				
Raw cohort variable	49.46	8.62	31.02	65.99
Residuals: net of degree and cohort FEs	0.00	1.67	-12.72	10.79
Quintile 5 (64–413 students)				
Raw cohort variable	49.65	8.40	30.06	63.19
Residuals: net of degree and cohort FEs	0.00	1.25	-10.74	4.91
B: Avg FLFP in province of origin of male peers				
Quintile 1 (<18 students)				
Raw cohort variable	48.88	9.00	29.87	66.66
Residuals: net of degree and cohort FEs	0.00	2.54	-16.56	11.13
Quintile 2 (18–27 students)				
Raw cohort variable	49.97	8.48	28.72	65.89
Residuals: net of degree and cohort FEs	0.00	2.40	-13.29	12.15
Quintile 3 (27–40 students)				
Raw cohort variable	50.29	8.39	29.49	65.33
Residuals: net of degree and cohort FEs	0.00	2.10	-16.12	9.92
Quintile 4 (40–64 students)				
Raw cohort variable	49.55	8.63	29.77	63.71
Residuals: net of degree and cohort FEs	0.00	1.98	-9.46	14.42
Quintile 5 (64–413 students)				
Raw cohort variable	49.78	8.46	27.33	66.37
Residuals: net of degree and cohort FEs	0.00	1.57	-9.61	11.78

Notes. The table reports descriptive statistics on average female labor force participation (FLFP) in the province of origin of female peers (Panel A) and male peers (Panel B). Statistics are presented by quintiles of degree size, defined based on the average number of students across cohorts. Student counts are reported in parentheses. The unit of observation is a degree–cohort pair, for a total of 7,160 observations.

Table A.XI: Peer Effects On Earnings And Labor Supply, Female Sample

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(hourly wage)
$\hat{\delta}^{FP}$	0.037***	0.033***	0.018**	0.004
	(0.013)	(0.012)	(0.009)	(0.012)
$\hat{\delta}^{MP}$	-0.000	0.001	-0.002	-0.001
	(0.010)	(0.009)	(0.007)	(0.010)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.287	0.246	0.280	0.099

Notes. OLS estimates of equation 2, regressing women's earnings and hours worked one year after graduation on the average FLFP in the provinces of origin of female and male peers. All specifications control for the FLFP in the student's own province of origin, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized. Differently from the baseline specification, this does not control for the proportion of female and male international students.

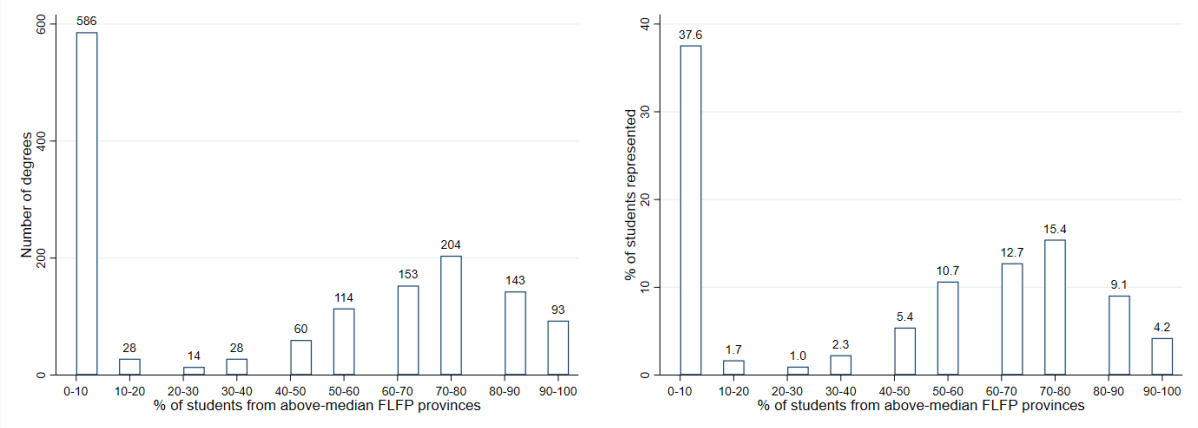
Table A.XII: Peer Effects On Earnings And Labor Supply, Female Sample

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(hourly wage)
$\hat{\delta}^{FP}$	0.036***	0.033***	0.018**	0.004
	(0.012)	(0.012)	(0.009)	(0.012)
$\hat{\delta}^{MP}$	-0.001	-0.000	-0.002	-0.001
	(0.010)	(0.009)	(0.007)	(0.010)
Province of origin FE	✓	✓	✓	✓
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.290	0.248	0.282	0.101

Notes. OLS estimates of equation 2, regressing women's earnings and hours worked one year after graduation on the average FLFP in the provinces of origin of female and male peers. All specifications control for the share of female and male international students in the program-cohort cell, as well as cohort, degree and province of origin fixed effects instead of linearly controlling for its FLFP rate. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Appendix B: Additional Figures

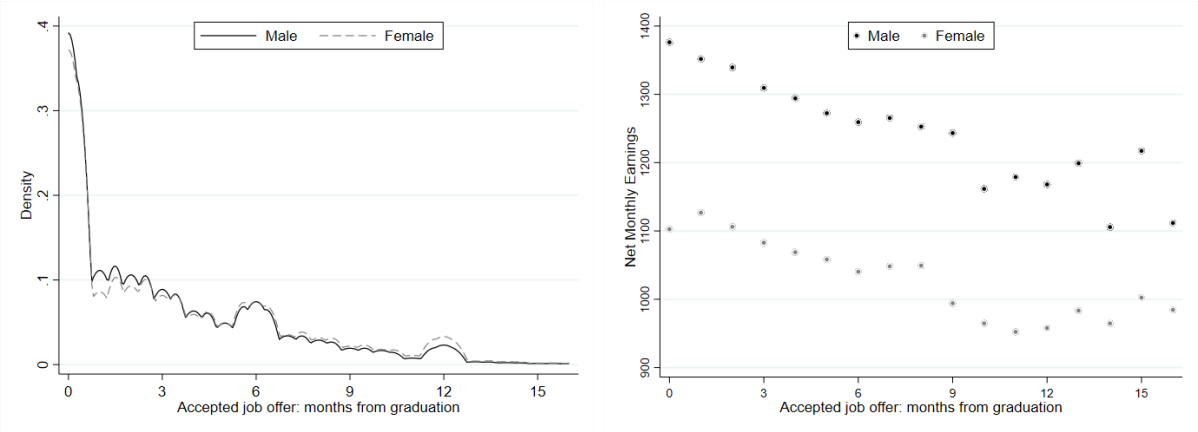
Figure A.I: Students from Above-Median FLFP Provinces Across Degree Programs



(a) Degrees **(b)** Students represented

Notes. These two graphs depict the distribution of students born in provinces with above-median FLFP across degree programs. Panel (A) shows the number of degrees (N = 1,572) falling into brackets based on the percentage of students from above-median FLFP areas in 2016: 0-10, ..., 90-100. One unit corresponds to a degree (N=1,572). Panel (B) displays the share of total students represented by degrees within each bracket. The distribution appears bimodal: 586 degree programs—enrolling approximately 37% of students—have between 0% and 10% of their students from above-median FLFP provinces. Among the remaining programs, the distribution is closer to normal, peaking in the 70–80% bracket.

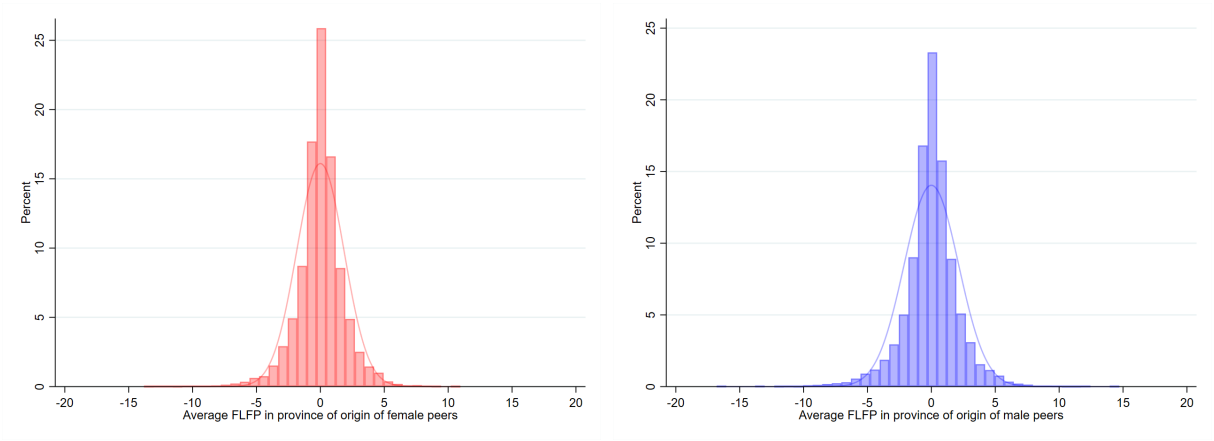
Figure A.II: Gender Gaps and the Timing of Job Acceptances



(a) Timing of job acceptances **(b)** Evolution of gender earnings gap

Notes. In both panels, men are shown in blue and women in red. Panel (A) displays the distribution of job acceptance timing, measured in months relative to the graduation date, for female and male graduates. A value of zero corresponds to jobs secured either prior to graduation or within the first month after graduation. Panel (B) plots average earnings of female and male workers by the month of job acceptance.

Figure A.III: Year-to-Year Variation in Students' Geographical Characteristics within Degrees



(a) Female peers (b) Male peers

Notes. The figure plots the distribution of residuals from an OLS regression of the average FLFP in the province of origin of female (Panel a) or male students (Panel b) on cohort and degree fixed effects. One observation corresponds to a degree–cohort pair. Histograms are presented using bins of width 0.75. A normal distribution is plotted for comparison.

Table A.XIII: Peer Effects On Earnings And Labor Supply, Female Sample - Alternative Specification

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(hourly wage)
$\hat{\delta}^{FP}$	0.036***	0.033***	0.018**	0.004
	(0.012)	(0.012)	(0.009)	(0.012)
$\hat{\delta}^{MP}$	-0.001	-0.000	-0.002	-0.001
	(0.010)	(0.009)	(0.007)	(0.010)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Province of origin FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.290	0.248	0.282	0.101

Notes. OLS estimates of equation 2, regressing women's earnings and labor supply one year after graduation on the average FLFP in the provinces of origin of female and male peers. Relative to the baseline specification, the student's own province-level FLFP is replaced by province-of-origin fixed effects. All specifications control for the share of female and male international students in the program-cohort cell, as well as cohort and degree fixed effects. The sample is restricted to Italian-born women employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Table A.XIV: Peer Effects on Occupations and Industries, Male Sample

	(1)	(2)	(3)	(4)	(5)
	Occupation		Industry		Log(weekly hours)
	High earn.	High full-time	High earn.	High full-time	
$\hat{\delta}^{FP}$	0.002	0.009	0.007	-0.013	-0.002
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)
$\hat{\delta}^{MP}$	0.008	-0.006	0.018*	0.019**	-0.009
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Job type FE					✓
Degree FE	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓
Observations	56,662	56,662	56,817	56,817	57,476
R-squared	0.340	0.472	0.275	0.403	0.346

Notes. OLS estimates of equation 2, regressing occupational and industry outcomes one year after graduation on the average FLFP in the provinces of origin of female and male peers and the FLFP in the student's own province of origin. The dependent variables in Columns (1) and (3) are binary indicators for whether a graduate works in an occupation or industry with above-median earnings, respectively. Those in Columns (2) and (4) are binary indicators for whether the occupation or industry has an above-median share of full-time employment. Column (5) re-estimates the effect on log weekly hours adding occupation fixed effects (20 classes) and industry fixed effects (21 classes). All specifications control for the share of female and male international students in the program-cohort cell, as well as cohort and degree fixed effects. The sample is restricted to Italian-born men employed one year after graduation with non-missing information on the relevant variables. Standard errors are clustered at the degree level. All regressors are standardized.

Appendix C: Variable Definitions

C.1 Parental Socioeconomic Status

Parental socioeconomic status (SES) is constructed from responses to the question: "What is/was your parent's most recent occupation?" Occupations are grouped into three categories:

High SES: Entrepreneur; self-employed professional (e.g., lawyer, doctor, accountant); manager, executive or senior official.

Medium SES: Teacher; mid-to-high skilled white-collar or intermediate worker (e.g., nurse, junior military officer); white-collar or intermediate worker.

Low SES: Self-employed worker, family helper, or cooperative member (managing shops, small businesses, or craft workshops involving manual labor); low-skilled white-collar or intermediate worker (e.g., telephone operator, shop assistant); blue-collar worker; homemaker.

C.2 Occupational and Industry Classifications

High-earnings occupations and industries. Occupations and industries are classified as high-earnings if the average monthly net earnings of graduates employed in that occupation or industry exceed the median.

High-earnings occupations:

- Entrepreneur, legislator, director, or senior manager
- Engineer or architect (senior)
- Lawyer, notary, or legal expert (in firms or public institutions)
- Physician (general practitioner or specialist; excludes psychologists)
- Software analyst or designer
- Expert in chemistry, physics, mathematics, or statistics
- Project manager, commercial expert, market analyst, communications manager, administrative officer, or other expert in management, business, or banking
- Junior architect, surveyor, computer programmer, statistical technician, chemical or mechanical engineer, electronics technician, or other technical professional in science and engineering
- Nurse, physiotherapist, health assistant (including dental hygienist, midwife, prevention technician), professional educator, or other expert in health and life sciences (e.g., agronomist, forestry technician, oenologist, food technician)

- Military officer

Low-earnings occupations:

- Psychologist or psychotherapist
- Journalist, interpreter, archivist, or other professional in linguistics, literature, or the arts
- Pharmacist or veterinarian (includes biologist, pharmacologist, zootechnician, agronomist, forestry expert)
- Teacher or professor (from primary school to university level; includes private tutors)
- Social, recreational, cultural, or sports technician (e.g., advertising graphic designer, tourist guide, social or cultural educator); public service or security professional (e.g., police or customs officer)
- Administrative employee, secretary, HR officer, or data entry operator
- Purchasing officer, payroll clerk, call center operator, counter clerk, or warehouse worker
- Retailer, shop assistant, waiter, or other qualified professional in commerce, personal services, or security (e.g., law enforcement agent, childcare worker, care home worker)
- Blue-collar worker or other unskilled occupation

High-earnings industries:

- Energy, gas, water, and mining
- Chemicals and petrochemicals
- Metalworking and precision mechanics
- Electronics and electrical engineering
- Other manufacturing
- Credit and insurance
- Information technology and data processing
- Healthcare (including local health authorities)

- Mail, transport, and travel
- Public administration and armed forces

Low-earnings industries:

- Agriculture, forestry, hunting, and fishing
- Printing and publishing
- Construction, design, installation, and building maintenance
- Commerce, hotels, and catering (including pharmacies)
- Advertising, communications, and telecommunications
- Legal, administrative, and accounting consulting
- Other consulting and professional services (including translation)
- Other business services (including temporary employment agencies)
- Education, training, research, and development (including schools, universities, and research institutes)
- Recreational, cultural, and sports services
- Other social and personal services

High full-time occupations and industries. Occupations and industries are classified as high full-time if the share of graduates employed full-time in that occupation or industry exceeds the sample median.

High full-time occupations:

- Entrepreneur, legislator, director, or senior manager
- Engineer or architect (senior)
- Lawyer, notary, or legal expert
- Expert in chemistry, physics, mathematics, or statistics
- Project manager, commercial expert, market analyst, communications manager, administrative officer, or other expert in management, business, or banking
- Junior architect, surveyor, computer programmer, statistical technician, or other technical professional in science and engineering

- Administrative employee, secretary, HR officer, or data entry operator
- Software analyst or designer
- Military officer

Low full-time occupations:

- Physician (general practitioner or specialist)
- Psychologist or psychotherapist
- Journalist, interpreter, archivist, or other professional in linguistics, literature, or the arts
- Pharmacist or veterinarian
- Teacher or professor
- Nurse, physiotherapist, or other expert in health and life sciences
- Social, recreational, cultural, or sports technician; public service or security professional
- Purchasing officer, payroll clerk, call center operator, or counter clerk
- Retailer, shop assistant, waiter, or other qualified professional in commerce or personal services
- Blue-collar worker or other unskilled occupation

High full-time industries:

- Energy, gas, water, and mining
- Chemicals and petrochemicals
- Metalworking and precision mechanics
- Electronics and electrical engineering
- Other manufacturing
- Construction, design, installation, and building maintenance
- Credit and insurance
- Legal, administrative, and accounting consulting

- Other consulting and professional services
- Information technology and data processing

Low full-time industries:

- Agriculture, forestry, hunting, and fishing
- Printing and publishing
- Commerce, hotels, and catering
- Mail, transport, and travel
- Advertising, communications, and telecommunications
- Other business services
- Public administration and armed forces
- Education, training, research, and development
- Healthcare
- Recreational, cultural, and sports services
- Other social and personal services